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The Empirics of Information Sharing in Supply Chains: The Case of the Food Industry

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Abstract

Using the Supermarket Panel Data gathered by The Food Industry Center at the University of Minnesota, the behavior of food retailers is examined in their adoption of Information Technologies that facilitate information exchange with suppliers. Using a theoretical framework developed by Mohtadi and Kinsey (MK) (2004) the predictions of that paper are examined. Logistic Regressions based on Maximum Likelihood Estimation support the hypothesis that food retailers with greater market power and numerous suppliers are more inclined to share, rather than to withhold, sales information. Stock-outs play a key role in the process as well. Finally, the structure of the market plays an interesting role in the type of information sharing platforms that the retailers adopt.

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Keywords: food industry, information, strategic behavior, supply chains, IT strategy

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INTRODUCTION

How do supermarkets, grocers, and other food outlets decide on the adoption of electronic commerce as a vehicle to share information with their supply chain partners and increase efficiency and predictability? What role does firm size and the structure of the supply chain play in this decision? This paper is aimed at answering these questions, based on econometric analysis of the 2003 Supermarket Panel data collected by The Food Industry Center at the University of Minnesota. The adoption of digital and Internet technology (IT) is credited for an otherwise unexplained increases in U.S. productivity during the 1990's. Understanding the nature of the changes and their impact on firm behavior and industry structure is crucial for public policy and corporate strategy. This issue is particularly important for the food industry: first, the food industry has been a leader in the IT initiatives for more than 30 years beginning with the initiative to design the scannable bar code. Secondly, the industry's thin profit margins could render cost-savings from the adoption of electronic commerce significant at the margin. Thirdly, the ever-evolving structure of this industry, with ongoing mergers and acquisitions, can be better understood in light of cost and market advantages made possible through the adoption of IT.

The underlying conceptual basis for this empirical project stems from a recent paper by Mohtadi and Kinsey (2005) (from now on, MK) that analyzed the *informational relationship* among firms along the food industry's supply chain using game theory modeling. It is also related to a second paper by Kauffman and Mohtadi (2004a) that extended the analytical model of MK (2005) and generalized it to other industries. These papers developed a number of hypotheses that will be presently tested. In this vein, the goal of this research is to empirically determine the *causes* and *incentives* that lead firms to adopt technologies that allow them to share information up the supply chains, rather than to explore the impact of technology adoption on productivity. There are several papers on the impact of IT on firm performance in the food industry (e.g., Dooley, Maud and King, 2004; and Kink and Park, 2002). But far fewer studies have focused on the causes and determinants of firms' technology adoption practices. This paper is aimed at filling this gap. In doing so, it will also provide empirical examination of the papers by MK (2005) and Kauffman and Mohtadi (2004a) in this area.

The history of IT adoption among food retailers in the U.S. begins with Wal-Mart's initiative to share daily sales data to reduce inventory and costs and develop inventory control strategies with key suppliers. In 1992, U.S. food retailers followed suit and developed an initiative known as Efficient Consumer Response (ECR). But this initiative faltered for two reasons; (a) the incompatibility of computer systems between retailers and suppliers, and (b) retailers' reluctance to share sales data directly with manufacturers. A later and similar initiative (1996), known as the Collaborative Planning, Forecasting, and Replenishment (CPFR) that involved retailers sharing sales data with the manufacturers (or wholesalers) in real time and often over the Internet (Kinsey, 2000), has helped to solve the first problem, i.e., the computer incompatibility problem, but has not resolved the second issue, i.e., the "trust" issue, arising from concern about *supplier opportunism*. In particular, some retailers fear that suppliers who learn of their inventory, sales, and ordering practices may somehow share this information with rivals or otherwise use it in ways that would diminish retailers' profitability (Kinsey and Ashman, 2000). This reluctance is also reported in Clemons and Row (1993), Progressive Gorcer (1995) and Nakayama (2000) and is at the root of the analytical model of MK.

In fact, in the food industry, Nakayama (2000) shows that information exchange plays a role in the power relationship between supermarkets and their suppliers, impacting their mutual trust and the adoption of information technology among firms. For example, when the food retailer uses electronic data interchange (EDI) for inventory coordination, the supplier's knowledge of retailer's parameters and strategies could lead to greater monitoring of retailer's sales and the timing of invoices and payments. This reduces the retailer's incentive to share its point of sale (POS) data directly with his supplier(s). This is a classic application of the ***asset hold-up*** problem: the retailer's fear of ex-post supplier opportunism reduces the retailer's incentive to invest in specific information sharing assets.[1] The trade-off between the need to share information and the need to protect information is best illustrated in the following question that the retailer asks: "What is the minimum set of information to share with my supply chain partners without risking potential exploitation?" (Lee and Whang 2000). Gal-Or (1985) showed how information withholding may be a Nash equilibrium outcome despite its social inefficiency.

In general, intimate knowledge of the market conditions is often buyer's strategic asset. But because suppliers may use such information against buyers, this tempers buyers' desire to adopt IT and risk losing competitive advantage in procurement (Whang, 1993). The result is that buyers have a diminished incentive to share information due to the risk of exposure (Laffont and Tirole, 1999), while still taking advantage of the strategic value of their private information

[1] See for example (Schmalensee and Willig, 1989), chps. 2,3,4.

(Chen, 1998; Gavirneni, et al., 1999). While the issue of information sharing horizontally, i.e., across firms, has been viewed in strategic settings for monopolistic, duopolistic, oligopolistic, and competitive structures (e.g., Gal-Or, 1985; Li, 1985 and 2002; Raith, 1996), the retailer reluctance to share information *vertically* along its supply chain, as opposed to horizontally, is tied to its concerns about supplier's potential for opportunistic behavior.[2] This is seen both from the above discussion of the evidence and the literature, but is also at the basis for the analytical model of MK. It occurs because the food retailer's adoption of information technologies would enable it to increase its procurement efficiency via its supply chain partners. This would, however, force it to share strategic and often valuable information (e.g., its knowledge of market forecasts) with suppliers that exposes the retailer to the suppliers' opportunistic behavior. But the MK paper also yields something new: *That a large retailer facing a large number of suppliers is less concerned about opportunistic supplier behavior, as the tendency for opportunistic behavior is more limited due to increased supplier competition.* This finding has an important implication which the present paper intends to examine. It predicts that such retailers are likely to be more willing to share information and thus adopt information sharing technologies with their suppliers than independent retailers facing a single or few large suppliers.

The next section discusses the analytical and the empirical framework. This is followed by a section on data and measurements issues. A subsequent section discusses the results, and the final section makes concluding remarks.

[2] For a more detailed survey of the related literature in industrial organization and management science, see Kauffman and Mohtadi (2004a).

ANALYTICAL AND EMPIRICAL MODELS

Analytical Model:

Two key insights from the MK (2005) constitute the main hypotheses that are tested in this paper. The first is represented by an equation that relates the food retailer's incentive to share information (and therefore adopt information sharing technologies), to the retailer's gains from information sharing. Of importance is the fact that the retailer's profits increase with the number of suppliers the retailer faces and the scale of demand (sales). Denoting net profits under information sharing arrangements by Γ_1*, MK (2005) find that:*

(1) $$\Gamma_1 = \frac{1}{4b}.(\frac{n}{n+1})^2 (a - c_o' - v)^2 - rF \ ,$$

where, n is the number of suppliers facing the retailer, a is the scale of demand, c_o is the operational cost associated with the product (documentation, transportation), v is the actual (manufacturing or processing) cost of the product, b is the slope of demand and rF represents the amortized (flow) cost of the fixed investments associated with information sharing IT adoption. It is cleat that,

(1a) $$\frac{\partial \Gamma_1}{\partial n} > 0 \text{ and } \frac{\partial \Gamma_1}{\partial a} > 0$$

The first result obtains because a large number of suppliers works to the advantage of the retailer by reducing supplier's ability to act opportunistically based on information it gathers from the retailer's market demand. Hence, large retailers facing numerous suppliers are more willing to adopt technologies and strategies that allow them to share information with their suppliers.

Notice that this is separate from the question of supplier size, *a*, which also exerts a positive influence on Γ_1. Thus, we have:

Hypothesis 1: Retailers with large sales and those facing a large number of suppliers are more willing to share sensitive market data along the supply chain with their suppliers.

The second insight addresses the reverse question by exploring the retailer incentive in *withholding* information. The *disincentive* to share information arises from concern for supplier opportunism despite obvious efficiency loss, such as reduced coordination of retailer-supplier orders and deliveries, that information withholding entails. Denoting such information withholding gains by Γ_2, it is found that Γ_2 depends on a number of firm and market characteristics. In particular,

(2) $$\Gamma_2 = \frac{\{\frac{n}{n+1}[a(1-\frac{1}{2}\Omega_{u<0}) - \frac{1}{2}s\Omega_{u>0} - (c_o' + v)] + \frac{1}{n+1}a\Omega_{u<0}\Omega^s_{d>0}\}^2}{4b(1-\Omega_{u<0})} - rF'$$

Here, in addition to the variables defined earlier, *s* is the storage cost. The terms involving Ω with various subscripts indicate the extent of unexpected supply and demand shocks that lead either to overstocks or stock-outs. Specifically, $\Omega_{u>0}$ represents "mean supply driven overstock" (hence the reason for being multiplied by s), while $\Omega_{u<0}$ and $\Omega^s_{d>0}$ represent the mean value of supply and demand driven stock-outs. As in equation 1, rF' represents the amortized (flow) cost of the fixed investments associated with IT adoption, but in this case IT is associated with technologies that enable the retail firm to exploit its information advantage over the supplier rather than to share information with the supplier. Examples might include the forecasting of demand or category management. As a result, the demand driven component of stock-out is eliminated (in theory entirely so) to the ***retailer***, but not to the supplier. Thus, as was mentioned earlier, large demand variability can actually benefit a retailer who is able to forecast its demand but would be otherwise vulnerable to supplier opportunism. Thus, we see from equation (2) that the gains form withholding information, Γ_2 , rise with stock-outs, $\Omega^s_{d>0}$, holding the number of suppliers (*n*) constant. But a rise in *n* reduces the incentive to withhold information (by reducing Γ_2) via the term involving stock-outs, $\Omega^s_{d>0}$. This is the ***information withholding effect*** and shows that information withholding pays less when the retailer has market power vis-a-vis many suppliers. Why is this? Withholding information from a supplier is aimed at preventing supplier opportunism, but a rise in the number of suppliers reduces supplier opportunism. Thus, gains from withholding information diminish. In fact, we can verify that,

(2a) $$\frac{\partial}{\partial n}\frac{\partial\Gamma_2}{\partial\Omega^s_{d>0}} < 0$$

Intuitively, a larger number of stock-outs represent great demand uncertainty. But such an uncertainty provides value to a retailer who can forecast the demand with some accuracy. When such a retailer is relatively small, the cost of supplier opportunism from sharing market demand data with a much larger supplier dominates the efficiency gains from such information sharing. Higher stock-outs imply higher value of demand prediction making it less likely that a small firm would adopt IT technologies that would lead to easier supplier opportunism. Examples of such supplier opportunism that are tied to the suppliers' knowledge of the retailers sales data might include suppliers offering excessively large "forward buys" to the retailers on the latter's "high demand" products that would help suppliers shed inventories, or refusing to pay promotion dollars for “fast moving” items since they would sell anyway, etc. As the firm faces an increasingly number of suppliers, concern for supplier opportunism is reduced due to increasing competition among suppliers.

This above discussion leads to second of key propositions of the MK (2005) that we present as hypothesis to be tested in this paper:

Hypothesis 2. Large food chains that face many suppliers are ***less*** *likely to withhold key market and stock-out data with their suppliers while small and independent retailers facing few large suppliers are more likely to withhold stock-out data.*

In the next sub-section we make operational the above hypotheses by presenting them in a testable empirical framework.

Empirical Model

Let, q be a binary variable such that,

(4a) $q = 1$ if an information sharing IT is adopted.

(4b) $q = 0$ if an information sharing IT is *not* adopted

Then from equation (1) the decision to adopt occurs if the profit Γ_1 exceeds some threshold profit level, Γ_1^*. Expressing this in terms of the probabilities (denoted by Prob.)

(5) $$\Pr ob(q = 1) = \Pr ob(\Gamma_1 > \Gamma_1^*) = f(n, a, \overline{X}) + e$$

Where e is an error term and *f* is increasing in the arguments, ***n*** and ***a*** and $\bar{X}$ is a vector of control variables. Then from the theoretical results (1a) we can see that hypothesis 1 would hold if the following two inequalities hold:

(6) Hypothesis 1: $\dfrac{\partial \Pr ob(q=1)}{\partial n} > 0$ and $\dfrac{\partial \Pr ob(q=1)}{\partial a} > 0$

Equation (2) yields results that are consistent with the above hypothesis. But as we see from (2a) this equation also yields an interesting result based on the interaction of the stock-out effect. To operationalize this equation, we note that the probability of withholding information, given the knowledge of the stock-out variable, can be expressed as:

(7) $$\Pr ob.(q=0|_{\Omega_{d>0}}) = \Pr ob.(\Gamma_2 > \Gamma_2^{\ *}) = g(n\Omega_{d>0}, \bar{Y}) + e'$$

Where $\Gamma_2^{\ *}$ is some threshold profit level, e' is an error term and $\bar{Y}$ is a vector of control variables. Given the result from equation (2a), we see that the interaction of the stock-out effect and the number of firms is such that g'<0 or that,

(8) $$\frac{\partial \Pr ob(q=0|_{\Omega_{d>0}})}{\partial(n\Omega^{s}_{d>0})} < 0$$

But note that this probability is *inversely* related to the probability of sharing information or that $\Pr ob(q=1|_{\Omega_{d>0}}) = 1 - \Pr ob(q=0|_{\Omega_{d>0}})$. From this, we can present an operational version of *Hypothesis 2*, as follows:

(9) Hypothesis 2: $\dfrac{\partial \Pr ob(q=1|_{\Omega_{d>0}})}{\partial(n\Omega^{s}_{d>0})} > 0$

The next section presents the empirical results.

DATA AND MEASUREMENTS

To test the above hypothesis, logistic regression is used because the choice of specific technology is a binary variable. The regressions are aimed at determining factors that influence the probability that a food retailer uses certain types of technologies that are likely to be associated with information sharing up the supply chain. The data is based on a subset of the 2003 survey of US supermarkets, consisting of 391 stores[3]. A list of the categories of both the dependent and the independent variables is given in Table 1.

As can be seen from the right hand side column in Table 1, several of the variables are converted from categorical to binary variables. The reasons for doing this are different for different variables. In the case of the IT variables, the clear issue is whether a technology is adopted or not. However, unlike the approach taken by Dooley, Maud, and King (2004) in which a single IT variable was created by adding up all the binary variables, the special focus of this paper on IT adoption suggests that a better approach in this case would be to keep the binary variables distinct and separate in order to maintain the specificity of each. (A detailed discussion of the technologies and their relation to information sharing strategies of the retail firm is presented in the next section.)

In the case of variable Q11 (relation of store to warehouse or supplier) the categorical variable is converted to two binary variables representing either membership in a self-distributing chain or having the warehouse as independent wholesale supplier. The interest in this dichotomous choice follows from a generally maintain hypothesis that self-distributing stores are more likely

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[3] The use of 391 stores, instead of over 890 original stores, is to allow for a consistent data set across the years 2000-2003 for later use as a panel data analysis.

to share information vertically since in this case, the supply chain, or at least a segment of it in this case, is *internal* to the firm. The stock-out variables in Q14 play an especially significant role in our empirical analysis based on the theoretical findings of the previous section. Here, an *average stock-out level* was calculated based on the simple average of the reported stock out variable in the three categories of cereal, poultry, and yogurt. Finally, horizontal market competition is thought to have an impact on a firm decision to share or not to share information with its suppliers as per Gal-Or, 1985; Li, 1985 and 1999; Raith, 1996. These variables are captured by sales or price leadership status of the store (Q27-SL=1 and Q29_PL=1) and by distance from the main competitor (Q25). Distance from one's competitor signals more insulation from the competitor making it more likely to allow the retailer to share it information with the supplier.

RESULTS

Results from Maximum Likelihood Estimation (MLE) of the logistic regression are presented in this section. Rather than using a broadly defined measure of supply chain technologies, we focus on three key technologies that form a critical role in *information sharing* processes; (a) the Electronic Transmission of Movement Data to headquarters or key suppliers (ETMD), (b) Scanning Data for Automatic Inventory Refills (SDAIR) and (c), Vendor Managed Inventory (VMI) consisting of vendor generated non-DSD (non-direct store delivery) orders via store movement data. Of these technologies, the first ETMD is a reflection of the retail firm's initiative and its *intention* in committing itself to share sensitive market or inventory information with its suppliers. On the other hand, the two other technologies, SDAIR and VMI entail a reduced level of retailer involvement and initiative: SDAIR involves automatic inventory refills and is therefore an automatic and routinized process; VMI involves vendor management of the retailer's data and therefore demands more initiative from the supplier than from the retailer. These observations have important implications for our empirical results. For example, we would expect stronger support for our hypothesis in the case of the ETMD technology than in the case of the other two technologies. This is because by focusing on the optimal choice of the retailer our theory presumed an active role on the part of the retailer while the supplier remained more or less passive with respect to the technology choice. This would be a better fit for the ETMD platform than for SDAIR or VMI platforms.

Of the independent variables, three are key variables that are associated with *Hypotheses 1* and *2*. These are store ***size*** by ***sales area***, the ***number*** of stores in the supply chain, and the extent of average ***stock-out*** that a store experiences. The two variables, "store size by sales area" and "number of stores in the supply chain" require some explanation. The variable "store size by sales area" is used as a proxy for the scale of demand denoted by "a" in the theory section. Although a variable known as "average weekly sales" by stores is also available from the Panel data, that variable is subject to a number of problems. Foremost among them is the fact that the time period over which the average is calculated is inconsistent across observations; varying from different months in 2002 to the year 2003. By contrast, store size by sales area is a more stable variable, even if measured in different months. It is therefore more likely to produce a consistent measure of sales, representing the scale of demand "a" more accurately.

The variable, "number of stores in the supply chain," indicates the size of the supply chain. In the absence of direct data on the number of suppliers which is needed to test *Hypotheses 1* and *2*, we shall use the variable, "number of stores in the supply chain," as a proxy for the number of suppliers. This is a plausible assumption as larger chains are able to exert market power over numerous small suppliers.[4]

Finally, a number of control variables are introduced that examine the importance of horizontal competition as well as the question of whether the store is part of a self-distributing chain or is served by a separate warehouse-wholesaler.

Testing Hypothesis 1

In what follows, tables 2 - 4 focus on the effects of store size and number of stores on the probability of adopting an information-sharing platform, as per *Hypothesis 1,* while Tables 5 - 6 focus on the effects of stock-out on that same probability as per *Hypothesis 2*. Other variables introduced in these tables play the role of various controls.

The structure of Tables 2 - 4 which report these direct effects is as follows: Tables 2 and 2a are associated with the ETMD technology. Table 2 reports the results for the *pooled* sample of all stores. In this table whether a store is part of a self-distributing chain or is an independent store, is captured by the dummy variable, "self-distributing." Although the sample also included a third category where the respondents "did not know" the store's status (see Table 1), the total

[4] One exception to this might be self-distributing stores which may elect fewer safer sources of supply to insure greater continuity. However, by carefully separating out this group of stores through either dummy variable or stratified sample, we are able to eliminate the potential for confounding that could arise from this effect. The author wishes to thank Jean Kinsey for this discussion.

number of such observations was only 3. Given this small size, it is safe to equate the base value of “self-distributing=0” to the case of independent stores. By contrast to Table 2, Table 2a reports the results of ***separate*** logistic regressions for two ***stratified*** sub-samples of self-distributing stores and independent stores. Similar structure is repeated in Tables 3 and 3a for the case of the SDAIR technology and Tables 4 and 4a for the case of VMI technology.

In Tables 2, 3, and 4, the first four columns represent four different logistic estimates, but focus only on the role of store size and vertical structure (i.e. self-distributing versus independent) as independent regressors. With respect to store size, both variables, sales area and total size, were highly correlated. Thus only one variable, in this case sales area, was chosen to be used in most of the regressions (except the first two), primarily because sales area is a closer index of the scale of demand (see equation 1) than is total store size.

The last two columns specify logistic regression runs that also add horizontal competition/market structure variables as control variables to the previous set. The difference between the two columns is that column E excludes the “self-distribution” dummy variable while column F includes that variable.

We will now discuss each table. Table 2 focuses on ETMD technology. This is the first of three supply chain technologies that is directly related to information sharing. From the table, store size by sales area is positively and significantly associated with the probability of adopting ETMD technology. However, the number of stores in the supply chain has a positive effect only when self-distribution is ***not*** controlled for and disappears in the presence of the self-distribution variable. In turn, self-distribution plays a strong and significant role in the technology adoption decision. But this would suggest that what appears to be as a confirmation of *Hypothesis 1* from Table 2, may be simply a reflection of the dominance of the self-distribution effect. We address this issue by stratifying the sample into self-distributing and independent stores. The results are reported in table 2a. Interestingly, both the number-of-stores variable and the size variable (our n and a in the theory section) are now significant for the *independent* store, but not for the self-distributing stores. Thus, it appears that both the number of stores and the size of store influence the probability of adopting EDTM technology. ; quite distinct from the self-distribution effect. In so far as EDTM technology is concerned, we therefore find *strong empirical support for Hypothesis 1*, where both the number of stores [as a proxy for the number of suppliers, (n) per earlier discussion] and the sort size (a) exert positive influence on the probability of adopting information sharing technologies.

The second technology that is directly involved in information sharing strategies is called Scanning Data for Automatic Inventory Refills (SDAIR). The results for this technology are reported in Table 3. These results are interesting in that in the pooled sample (Table 3) both size and the number of stores are significant whether or not the self-distribution variable is present. However, in the stratified sample (Table 3a) the size variable and the number-of-stores variable both lose significance for independent stores while only the size variable remains significant for self-distributing chains. Econometrically, this outcome can occur if, in the pooled sample, the residuals are correlated with the dummy variable "self-distribution" (e.g., a systematically higher or systematically lower residual for the self-distributing chains). In that case, the stratified sample resolves this problem by running separate logistic regressions on each of the two sub-samples. Thus, on the whole, the results of Table 3a are to be trusted more. Here, the coefficients of size are significant only in two instances and those of the "number of stores variables" are only border-line significant (see below for our explanation.)

Next, we will focus on a third type of information sharing technology, namely, Vendor Managed Inventory (VMI) consisting of vendor generated non-DSD orders via store movement data. A comparison of Tables 4 and 4a shows a rather similar pattern as the one for the SDAIR technology, where the significance of the number-of-stores in Table 4 in the pooled sample disappears in the stratified sample and where the size variable loses significance in the stratified sample. In short, we observe *weak support for Hypothesis 1 in the case of SDAIR and VMI technologies and strong support for that hypothesis in case of ETMD technology*.

All three findings above, the strong support of *Hypothesis 1* for the ETDM technology and the weak support for that hypothesis for SDAIR and VMI technologies are entirely consistent with the fact that ETDM involves the retailer's active participation while the other two technologies are those in which the initiative is with the supplier and not the retailer. This observation was earlier discussed in greater detail. It will be further reinforced when we test *Hypothesis 2* below.

Testing Hypothesis 2:

We can test *Hypothesis 2* by considering the role that stock-outs play in influencing the stores decision to adopt information sharing technologies with their suppliers. Equation (9) indicated that the likelihood of adopting information sharing technologies by a retailer increases with the product "$n.\Omega_\delta$", where n is the number of suppliers and Ω_δ is the mean value of stock-outs.

Again, using the variable "number of stores in the chain," as a proxy for the number of suppliers under *Hypothesis 2*, results of testing for this hypothesis are reported in Tables 5 and 5a. Accordingly, the critical variable to look for is the interaction variable, "Average_stockout **X** number of stores." On this variable, Table 5 shows the indicated positive and significant sign, but only for the VMI technology. However, since "self-distribution" does not enter in this table as a dummy variable, it is hard to gauge whether this positive effect is associated with self-distributing stores or independent retailers. Table 5a is therefore presented in which the various runs of table 5 are repeated for the *stratified* samples of self-distributing stores and independent stores. For the case of VMI technology, the results from Table 5a reiterate the significant and positive sign of the key interaction variable, "Average_stockout **X** number of stores," that was found in Table 5. *Thus results for the VMI technology support Hypothesis 2, but are found only among the self-distributing stores.* In addition, Table 5a reveals a new pattern that was not observed in the pooled sample of Table 5: our key interaction variable is found to be significant and positive for the case of the ETDM technology among *independent* food retailers. *Thus results for the ETMD technology support Hypothesis 2, but only for independent food retailers.* What makes these results interesting is the fact that *different* technologies appear to be associated with information sharing under *different* market structures. The explanation for this lies in understanding the meaning of the interaction variable when combined with the characteristics of the technologies. Our theory section showed that stock-outs trigger a need to share technologies to minimize their level and their adverse effects on profits. But at the same time, retailers are also concerned about the potential for exploitation of their information by the suppliers. The more numerous are the suppliers (empirically approximated the size of the retail chain), the less is the retailer distrust of the supplier and the more likely are retailers to adopt information sharing technologies with their suppliers. What ties this hypothesis to the technology platform is the question of how much of a choice *does* the retailer exercise in its technology adoption decision. The ETDM technology involves, by its definition, the transmission of data *by the retailer* and thus much involves retailer initiative and choice. Such a decision requires much autonomy and independence. This is the characteristic of independent retailers, rather than retailers that are a part of self-distributing chains where critical decisions are taken at corporate headquarters. By contrast, the VMI technology involves vendor management of information and is likely to involve a great deal of supplier initiative. Thus, it is more likely to be initiated at a company-wide level and at headquarters and is therefore more likely to be associated with self-distributing stores.

In short, the nature of information sharing technology platforms in the food industry is highly influenced by the specific market structure of the firms involved.

Finally, Table 5a tells us that store size is also important in technology adoption decisions. It is an important determinant for independent stores for the ETMD and VMI technologies and for self-distributing stores for SDAIR and VMI technologies.

CONCLUSION

Vertical information sharing has posed a sensitive strategic challenge among retail firms who, by their location at the end of the supply chain, possess the most valuable segment of the information real estate and one that is valuable to all members of the supply chain. The challenge is this: on the one hand information sharing increases the efficiency of the retailers by better coordinating supplies and orders, and on the other hand, it may compromise the bargaining power of the retailers, opening them to opportunistic behavior on the part of suppliers.

Nowhere is this dilemma more apparent than in the food sector. Basing its theoretical framework on a paper by Mohtadi and Kinsey (2005) and its empirical analysis on the Supermarket Panel Data conducted by The Food Industry Center at the University of Minnesota, this paper examines this issue. The empirical results generally support the theory, but point to a dichotomy: firms that are part of larger chains are more likely to adopt technologies leading to vertical sharing of information, but firms that belong to smaller chains are less likely to do so. The fundamental explanation for this finding does ***not*** seem to be the cost and the affordability of the technology. Such effects are already controlled for by variables such as store size and yet, significant residual effects remain. The MK (2005) paper and Kauffman and Mohtadi (2004a) papers argued that opportunistic behavior on the part of agents (in this case, the suppliers) is responsible for this result and the empirical findings here seem to point to that direction.

Thus, there appears to be a “digital divide in information sharing” between the two types of market structures. This divide, however, is distinct from the issue of cost of IT adoption and the question of its affordability by smaller stores and stems from issues related to incomplete markets. Kauffman and Mohtadi (2004b) analyzed a related divide between large and small firms in terms of the types of procurement technology that they adopt. The findings in this paper also shed light on how different market structures adopt different types of technologies. This is consistent with Kauffman and Mohtadi (2004b).

Are there public policy implications of these findings; both with respect to adoption versus non-adoption of IT platforms as well as with respect to the adoption of different types of platforms? Should there be regulatory mechanisms that are aimed at evening out the playing field? These are among some of the questions that this paper raises, but does not answer. Yet, such answers must be sought if further concentration of the food industry is likely to continue.

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Table 1: Description of Select variables from 2003 Supermarket Survey University of Minnesota- The Food Industry Center

Variable Codes*	**Information Technologies (IT) involving information sharing:**	**Original Form of the Var. in Survey:**	**Variables converted for this research:**

Q1d	Electronic transmission of movement data to headquarters or key suppliers (ETMD)	These variables were in categorical form as follows:
		
		Used >3 years=1
		
		Used 1-2 years=2
		
		Used 1 yr=3
		
		Plan to use next year=4
		
		No plan to use=5
		
		Do not know=6
			The variables were converted to binary variables, Q1d-adopt…
			Q1*l*-adopt. for use in logistic regressions:
			
			If Q1d…Q1*l* = 1, 2, or 3, then
			Q1d-adopt…Q1*l*-adopt =1, i.e., technology is adopted.
			
			If Q1d…Q1*l* = 4, 5, or 6, then
			Q1d-adopt…Q1*l*-adopt =0, i.e., technology is not

Q1g	Internet/Intranet link to corporate headquarters and/or key suppliers		
Q1i	Scan-based trading (payment to vendor triggered by sale to consumer)		
Q1j	Scanning data for automatic inventory refill (SDAIR)		
Q1*l*	Vendor managed inventory (vendor generated non-DSD orders via store movement data) (VMI)		
	Size Variables:		
Q4	Selling area		
Q5	Total area		
	Vertical Structure:		
Q10	# of stores in the supply chain		
Q11	*Relation of store to warehouse or supplier:*	Categorical Variables:	Binary variable Q11-Selfdis is created:
	Store uses a wholesaler	Q11=1	Q11-Wohlesale=1 if Q11=1 Q11-Wohlesale=0 otherwise Q11-Selfdist=1 if Q11=2 Q11-Selfdist=0 otherwise
	Store is part of self-distributing chain	Q11=2	
	Unknown	Q11=3	
	Stock-out Problem:	Categorical Variables:	Binary variables are created:
Q14a	Cereal	large problem: Q14a=1 small problem: Q14a =2 No problem: Q14a =3 Not known; Q14a =4 Same for Q14b & Q14c.	Q14a-stkout=1 if Q14a=1,2 Q14a-stkout=0 if Q14a=3,4 Same for Q14b and Q14c.
Q14b	Poultry		
Q14c	Yogurt		
	Horizontal Competition:		
Q25	Distance from the main competitor		
Q27 (10)	Competitive sales rank of the four main competitors (1- 4: Leader=1)	Q27 = 1 if self is leader Q27=2-4 if others	Q27-SL =1 if Q27=1 Q27-SL = 0 if Q27=2-4
Q29	Price leadership of store & its 3 main competitors	Q29 = 1 if self is leader Q29=2-4 if others	Q29-PL =1 if Q27=1 Q29-PL = 0 if Q27=2-4

* The codes are those actually used in the Supermarket Panel (2003) survey itself.

Table 2: Maximum Likelihood Logistic Estimates of the Effects of Store and Market Characteristics on the Probability of Adopting ETMD (Electronic Transmission of Movement Data to Head Quarters/Suppliers)
(test of hypothesis 1)

Pooled Sample

	Dependent Variable: Probability (ETMD adopt=1)					
	A	B	C	D	E	F
Size Variables						
Sales area (in 1000 sq feet)	1.030	1.031	**1.055****	**1.043****	**1.05****	**1.040****
	(0.97)	(1.03)	**(6.23)**	**(4.63)**	**(5.21)**	**(4.12)**
Total Size (in 1000 sq feet)	1.024	1.013				
	(0.97)	(0.53)				
Vertical Supply Chain Structure						
Number of stores (in 10 store units)	**1.008****	1.004	**1.009****	1.004	1.008	1.004
	(2.31)	(1.19)	**(2.5)**	(1.23)	**(2.35)**	(1.08)
Self-distributing		**3.020****		**3.430****		**3.538****
		(3.21)		**(3.66)**		**(3.48)**
Horizontal Competition/Market Structure						
Distance to first competitor					**0.970***	0.979
					(-1.66)	(-1.39)
Sale-leader (self)					**1.860***	1.174
					(1.67)	(1.38)
Price-leader (self)					0.980	0.763
					(-0.06)	(-0.82)
Log likelihood	-201.9	-196.4	-207.0	-199.8	-193.3	-186.8
Pseudo R2	0.18	0.21	0.17	0.20	0.19	0.22

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
* means significant at 10 percent or better
** means significant at 5 percent or better

Table 2a: Same as Table 2 but for Stratified Samples of Self-Distributing and Independent Stores
(test of hypothesis 1)

	Dependent Variable: Probability (ETMD adopt=1)					
	Columns A-C: Subsample of Self-Distrubuting Stores			Columns D-F: Subsample of Independent Stores		
	A	B	C	D	E	F
Size Variables						
Sales area (in 1000 sq feet)	1.053	1.029	1.023	0.978	**1.026****	**1.026****
	(1.14)	(1.76)	(1.32)	(-0.51)	**(2.30)**	**(2.15)**
Total Size (in 1000 sq feet)	0.981			1.045		
	(-0.51)			(1.25)		
Vertical Supply Chain Structure						
Number of stores (in 10 store units)	1.002	1.002	1.002	**1.588****	**1.584****	**1.574****
	(0.66)	(0.65)	(0.69)	**(2.77)**	**(2.81)**	**(2.74)**
Horizontal Competition/Market Structure						
Distance to first competitor			1.008			0.982
			(0.07)			(-1.15)
Sale-leader (self)			**4.09***			1.389
			(1.71)			(0.67)
Price-leader (self)			0.642			0.667
			(-0.76)			(-0.92)
Log likelihood	-49.8	-50.5	-45.7	-39.3	-137.8	-129.8
Pseudo R2	0.05	0.05	0.09	0.05	0.15	0.16

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
* indicates marginal significance at 10 percent or better
** means significant to 5 percent or better

Table 3: Maximum Likelihood Logistic Estimates of the Effects of Store and Market Characteristics on Probability of Adopting SDAIR (Scanning Data for Automatic Inventory Refill)
(test of hypothesis 1)

Pooled Sample

Dependent Variable: Probability (SDAIR adopt=1)

	A	B	C	D	E	F
Size Variables						
Sales area (in 1000 sq feet) Q4/1000	0.980	0.980	**1.0298****	**1.0257****	**1.0259****	**1.0241****
	(-0.68)	(-0.58)	**(4.01)**	**(3.38)**	**(3.46)**	**(3.15)**
Total Size (in 1000 sq feet) Q5/1000	1.045	1.040				
	(1.69)	(1.45)				
Vertical Supply Chain Structure						
Number of stores (in 10 store units) Q10/10	**1.005****	**1.004****	**1.005****	**1.004***	**1.005**	1.004
	(2.69)	**(1.87)**	**(2.62)**	**(1.71)**	**(2.35)**	(1.62)
Self-distributing		1.967		2.161		1.781
		(1.43)		(1.66)		(1.18)
Horizontal Competition/Market Structure						
Distance to first competitor					0.911	0.918
					(-1.38)	(-1.25)
Sale-leader (self)					1.366	1.313
					(0.64)	(0.57)
Price-leader (self)					0.629	0.583
					(-0.95)	(-1.1)
Log likelihood	-96.9	-95.9	-98.9	-97.5	-91.8	-91.1
Pseudo R2	0.18	0.19	0.16	0.18	0.18	0.19

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
*means significant at 10 percent or better
**means significant to 5 percent or better

Table 3a: Same as Table 3 but for Stratified Samples of Self-Distributing and Independent Stores
(test of hypothesis 1)

	Dependent Variable: Probability (ETMD adopt=1)					
	Columns A-C: Subsample of Self-Distrubuting Stores			Columns D-F: Subsample of Independent Stores		
	A	B	C	D	E	F
Size Variables						
Sales area (in 1000 sq feet)	0.99	**1.028****	**1.028****	0.95	1.02	1.01
	(-0.24)	**(3.07)**	**(3.01)**	(-0.70)	(0.90)	(0.49)
Total Size (in 1000 sq feet)	1.03			1.06		
	(1.02)			(1.01)		
Vertical Supply Chain Structure						
Number of stores (in 10 store units)	1.00	1.00	1.00	1.01	1.01	1.01
	(1.60)	(1.46)	(1.42)	(1.36)	(1.52)	(1.21)
Horizontal Competition/Market Structure						
Distance to first competitor			0.98			0.88
			(-0.18)			(-1.28)
Sale-leader (self)			1.18			1.31
			(0.29)			(0.30)
Price-leader (self)			0.51			0.99
			(-1.16)			(-0.01)
Log likelihood	-56.0296	-56.952	-52.2752	-39.2822	-39.9132	-37.7619
Pseudo R2	0.15	0.14	0.16	0.05	0.04	0.08

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
** means significant to 5 percent or better

Table 4: Maximum Likelihood Logistic Estimates of the Effects of Store and Market Characteristics on the Probability of Adopting VMI (Vendor Managed Inventory)
(test of hypothesis 1)

Pooled Sample

	Dependent Variable: Probability (VMI adopt=1)					
	A	B	C	D	E	F
Size Variables						
Sales area (in 1000 sq feet)	1.007	1.009	**1.022****	**1.019****	**1.022****	**1.019****
	(0.30)	(0.37)	**(3.58)**	**(3.01)**	**(3.26)**	**(2.88)**
Total Size (in 1000 sq feet)	1.013	1.009				
	(0.61)	(0.42)				
Vertical Supply Chain Structure						
Number of stores (in 10 store units)	**1.004****	1.003	**1.004****	1.003	**1.004****	1.003
	(2.14)	(1.51)	**(2.16)**	(1.52)	**(2.35)**	(1.59)
Self-distributing		1.458		1.469		1.598
		(1.16)		(1.21)		(1.35)
Horizontal Competition/Market Structure						
Distance to first competitor					1.010	1.013
					(0.90)	(1.08)
Sale-leader (self)					1.145	1.085
					(0.37)	(0.23)
Price-leader (self)					0.901	0.848
					(-0.28)	(-0.48)
Log likelihood	-176.195	-175.529	-177.763	-177.044	-165.498	-164.594
Pseudo R2	0.08	0.08	0.08	0.08	0.08	0.09

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
** means significant to 5 percent or better

Table 4a: Same as Table 4 but for Stratified Samples of Self-Distributing and Independent Stores
(test of hypothesis 1)

	Dependent Variable: Probability (ETMD adopt=1)					
	Columns A-C: Subsample of Self-Distrubuting Stores			Columns D-F: Subsample of Independent Stores		
	A	**B**	**C**	**D**	**E**	F
Size Variables						
Sales area (in 1000 sq feet)	1.01	**1.018****	**1.02****	1.00	**1.02***	1.02
	(0.43)	**(2.38)**	**(2.42)**	(0.11)	**(1.81)**	(1.56)
Total Size (in 1000 sq feet)	1.00			1.01		
	(0.15)			(0.43)		
Vertical Supply Chain Structure						
Number of stores (in 10 store units)	1.00	1.00	1.00	1.01	1.01	1.01
	(1.37)	(1.39)	(1.52)	(0.72)	(0.79)	(0.90)
Horizontal Competition/Market Structure						
Distance to first competitor			1.08			1.01
			(1.20)			(0.92)
Sale-leader (self)			1.26			0.70
			(0.49)			(-0.56)
Price-leader (self)			0.52			1.97
			(-1.42)			(1.39)
Log likelihood	-79.065	-80.014	-72.5	-96.3244	-96.9266	-89.0611
Pseudo R2	0.064	0.065	0.101	0.0245	0.0216	0.0322

Notes: Estimates are odds ratios
Numbers in parenthesis are z values.
* indicates marginal significance at 10 percent or better
**means significant to 5 percent or better

Table 5: Maximum Likelihood Logistic Estimates of the Effects of Stockouts and number of Stores on the Probability of Adopting Different Technolgies

(test of hypothesis 2) **Pooled Sample**

Dependent Variables: Probability of Adopting the Technology

	ETMD (Elect.Trans. of Movement Data…		SDAIR (Scanning Data for Auto. Inventory Refill)		VMI (Vendor Managed Inventory) (Non-SDS)	
Size						
Sales area (in 1000 sq feet)	**1.050****	**1.050****	**1.028****	**1.027****	**1.025****	**1.024****
	(5.26)	**(5.25)**	**(3.82)**	**(3.75)**	**(3.76)**	**(3.72)**
Horizontal Competition						
Distance from the main competitor	**0.974***	**0.973***	0.907	0.905	1.010	1.009
	(-1.7)	**(-1.77)**	(-1.43)	(-1.44)	(0.80)	(0.74)
Competitive sales rank of main competitor	1.755	**1.93***	1.303	1.331	1.125	1.161
	(1.50)	**(1.72)**	(0.55)	(0.59)	(0.32)	(0.41)
Price leadership of the store against its 3 main competitors	0.894	0.848	0.612	0.588	0.923	0.891
	(-0.36)	(-0.52)	(-1.00)	(-0.89)	(-0.23)	(-0.34)
Stock-out Effects						
Average_Stockout		**0.405****		0.515		0.563
		(-2.31)		(-0.89)		(-1.19)
Average_stockout **X** number of stores (in 10s)	0.999	0.999	1.004	1.005	**1.007***	**1.007****
	(-0.18)	(-0.06)	(1.08)	(1.13)	**(1.84)**	**(1.90)**
Average_stockout **X** self distribution	**5.802**	**8.772**	1.712	2.554	0.750	1.024
	(2.29)	**2.820**	(0.74)	(1.07)	(-0.46)	(0.03)
	-193.1	-190.37898	-92.3	-91.890	-166.1	-165.3
	0.194	2.820	0.176	0.179	0.078	0.205

Notes: Estimates are odds ratios

Numbers in parenthesis are z values

* indicates marginal significance at 10 percent or better

**means significant to 5 percent or better

Table 5a: Same as Table 5 but for Stratified Samples of Self-Distributing and Independent Stores
(test of hypothesis 2)

Dependent Variables: Probability of Adopting the Technology

	ETMD (Elect.Trans. of Movement Data…		SDAIR (Scanning Data for Auto. Inventory Refill)		VMI (Vendor Managed Inventory) (Non-SDS)	
	subsample: self-dist. stores	subsample: indep. stores	subsample: self-dist. stores	subsample: indep. stores	subsample: self-dist. stores	subsample: indep. stores
Size						
Sale area (in 1000 sq feet)	1.025	**1.034****	**1.030****	1.009	**1.023**	**1.022***
	(1.42)	**(2.76)**	**(3.28)**	(0.48)	**(2.74)**	**(1.84)**
Horizontal Competition						
Distance from the main competitor	0.989	0.982	0.977	0.878	1.084	1.011
	(-0.1)	(-1.19)	(-0.24)	(-1.28)	(1.13)	(0.83)
Competitive sales rank of main competitor	**4.015***	1.408	1.120	1.337	1.256	0.718
	(1.69)	(0.67)	(0.20)	(0.32)	(0.48)	(-0.50)
Price leadership of the store against its 3 main competitors	0.609	0.741	0.503	0.838	0.521	2.031
	(-0.85)	(-0.69)	(-1.17)	(-0.20)	(-1.40)	(1.43)
Stock-out Effects						
Average_Stockout	1.182	**0.386****	1.034	0.887	0.313	1.11
	(0.18)	**(-1.96)**	(0.04)	(-0.12)	(-1.55)	(0.18)
Average_stockout **X** number of stores (in 10s)	0.999	**2.424****	1.004	1.033	**1.008****	0.958
	(-0.17)	**(2.02)**	(1.04)	(1.14)	**(2.04)**	(-0.79)
Log likelihood	-45.94	-132.12	-52.460	-37.817	-71.3	-88.91
Pseudo R2	0.086	0.141	0.153	0.075	0.116	0.034

Notes: Estimates are odds ratios
Numbers in parenthesis are z values
* indicates marginal significance at 10 percent or better
** means significant to 5 percent or better