ABSTRACT

Title of dissertation: ESSAY ON SUPPLY CHAIN FINANCE

Weiming Zhu, Doctor of Philosophy, 2016

Dissertation directed by: Professor Tunay Tunca
Department of Decision, Operations
& Information Technologies

I study how a larger party within a supply chain could use its superior knowledge about its partner, who is considered to be financially constrained, to help its partner gain access to cheap finance. In particular, I consider two scenarios: (i) Retailer intermediation in supplier finance and (ii) The Effectiveness of Supplier Buy Back Finance.

In the fist chapter, I study how a large buyer could help small suppliers obtain financing for their operations. Especially in developing economies, traditional financing methods can be very costly or unavailable to such suppliers. In order to reduce channel costs, in recent years large buyers started to implement their own financing methods that intermediate between suppliers and financing institutions. In this paper, I analyze the role and efficiency of buyer intermediation in supplier financing. Building a game-theoretical model, I show that buyer intermediated financing can significantly improve supply chain performance. Using data from a large Chinese online retailer and through structural regression estimation based on

the theoretical analysis, I demonstrate that buyer intermediation induces lower interest rates and wholesale prices, increases order quantities, and boosts supplier borrowing. The analysis also shows that the retailer systematically overestimates the consumer demand. Based on counterfactual analysis, I predict that the implementation of buyer intermediated financing for the online retailer in 2013 improved channel profits by 18.3%, yielding more than $68M projected savings.

In the second chapter, I study a novel buy-back financing scheme employed by large manufacturers in some emerging markets. A large manufacturer can secure financing for its budget-constrained downstream partners by assuming a part of the risk for their inventory by committing to buy back some unsold units. Buy back commitment could help a small downstream party secure a bank loan and further induce a higher order quantity through better allocation of risk in the supply chain. However, such a commitment may undermine the supply chain performance as it imposes extra costs on the supplier incurred by the return of large or costly-to-handle items. I first theoretically analyze the buy-back financing contract employed by a leading Chinese automative manufacturer and some variants of this contracting scheme. In order to measure the effectiveness of buy-back financing contracts, I utilize contract and sales data from the company and structurally estimate the theoretical model. Through counterfactual analysis, I study the efficiency of various buy-back financing schemes and compare them to traditional financing methods. I find that buy-back contract agreements can improve channel efficiency significantly compared to simple contracts with no buy-back, whether the downstream retailer can secure financing on its own or not.

ESSAYS ON SUPPLY CHAIN FINANCE

by

Weiming Zhu

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2016

Advisory Committee:
Professor Tunay Tunca, Chair/Advisor
Professor John Chao
Professor Zhi-Long Chen
Professor Ilya Ryzhov
Professor Yi Xu

Acknowledgments

I owe my gratitude to all the people who have made this thesis possible and because of whom my graduate experience has been one that I will cherish forever.

First and foremost I'd like to thank my advisor, Professor Tunay Tunca for giving me an invaluable opportunity to work on challenging and extremely interesting topics over the past three years. As a source of knowledge, inspiration and professionalism, he has always made himself available for help and advice and there has never been an occasion when I've knocked on his door and he hasn't given me time. It has been a pleasure to work with and learn from such an extraordinary individual.

Also my thesis committee guided me through all these years. Thank you Wedad Elmaghraby, Ilya Ryzhov for teaching me two fantastic courses. Thank you Zhi-Long and Yi Xu for all the valuable guidance in my first two years. Also thank you to John Chao for being the dean's representative in my committee, a thesis reader who gives great suggestions, and an inspiration in many ways.

I would like to thank Jiaming Sun, Yuduo Fuzhen, Jun Huang and JD.com's data team for providing us the comprehensive dataset as well as their clarification for the financing scheme employed by JD.com's financing devision. Also, I thank Bin Yang for helping me get access to multiple companies and obtain data from them.

I owe my deepest thanks to my family - my mother and father who have always stood by me and guided me through my career, and have pulled me through against impossible odds at times. Words cannot express the gratitude I owe them. Also, my special thanks go to my girlfriend, Ran Li. Her understanding and support are what encourage me to finish the dissertation smoothly. I thank my best friends Tianshu Sun and Liu Ming for the inspiration and support they provided, it feels great to pursue the Ph.D. journey with you two.

It is impossible to remember all, and I apologize to those I've inadvertently left out.

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Chapter 1: Introduction

1.1 An Overview of Supply Chain Finance

The thrive of SMEs are crucial to the thrive of the economy. However, among many factors that hinder the growth of SMEs, the lack of access to cheap finance is a particularly severe one that undermines the success of SMEs. Financing SMEs in developing country is especially challenging for bank due to the lack of credit history, the lack of collateral and also the lack of tailored financing scheme. As a result, SMEs often resort to expensive loan provided by private loan firms. Both the inability of obtaining external financing and the high interest rate pose difficulty for the operation of the firm and its partners. Specifically, within a supply chain, a financially constrained party could do damage to its upstream and downstream in the form of late delivery, underproduction and inferior supply chain efficiency.

Recently, realizing that the transaction history with the budget constrained party could serve as a measure for gauging the creditworthiness, large party within the supply chain starts to employ their superior knowledge about the small party and design novel financing schemes that could help the capital constrained party to obtain cheap finance by either reallocating the risk within the supply chain or underwriting the small party. We study how could larger party within a supply chain could use its superior knowledge about its partner, who is small and is considered to be financially constrained, to help its partner gain access to cheap finance. We consider two scenarios: (i) Retailer intermediation in supplier finance and (ii) supplier buy back finance.

Chapter 2: Retailer Intermediation in Supplier Finance

2.1 Introduction

When providing goods to a downstream retailer, suppliers often bear a long payment delay after delivery. Usually, this delay is contractually imposed by the buyer due to reasons that span from retailer financing to quality control and payments being contingent on the products being defect-free. As a consequence, suppliers, especially small ones, often find themselves in need of cash and financing in order to support their operations. However, it is often very difficult for small suppliers to obtain financing under favorable conditions. The situation is worse in developing economies such as China, due to lack of credit history, and in certain cases, lack of established financial mechanisms. As a result, suppliers often resort to loans with very high interest rates, which increase the overall costs in the supply chain and reduce channel efficiency.

Concerned about the rising supply chain costs and the difficulty, and sometimes inability, of their suppliers to receive financing, buyers are stepping up to help mitigate their suppliers' cash flow problems. Different companies take different approaches to the problem but in many cases, buyers employing these new schemes essentially act as intermediaries or underwriters, with a third-party bank lending money to the supplier. Usually, with their knowledge of historical transaction details and their past interactions with their suppliers, buyers have better information about the reliability of their own suppliers than banks do. This allows them to bridge the gap between a bank and the supplier, secure the loan back payment and price the supplier risk more efficiently. As a result, the bank can lend to the supplier at a better rate, the supplier can have his operations financed and the entire channel can operate more efficiently.

One example of a large buyer who provides financing intermediation to its suppliers is the Chinese online retailing giant JD.com (formerly named Jingdong and henceforth JD in the paper). JD is currently China's largest online retailer offering more than a million product selections of thousands of brands with an annual sales volume of approximately \$12 Billion. JD's suppliers vary in size and many are small suppliers who are routinely in need of financing to continue their operations. To ease supplier financing costs, JD launched a supplier finance intermediation service in 2012. The financing scheme works as follows: JD and a supplier agree on delivery of goods at a future date with JD's payment to the supplier being due after a certain period, e.g., 45 days. However, often the supplier needs cash earlier than the payment due date to cover its operational costs and continue production. To provide this financing, JD intermediates between the supplier and a third-party bank. In particular, the bank provides a part of the payment determined by the supplier, but charges a certain percentage of that amount, determined by JD, to the supplier as "prepaid interest". In return, JD guarantees the payment of the full amount to the bank at the due date. In doing so, JD effectively underwrites the loan, assumes the supplier defect risk, and frees the bank of any concerns that a loan will not be paid back. This arrangement significantly reduces the cost of financing for the supplier as it reduces the riskiness of the loan for the bank. At the time scheduled for the payment, in addition to paying the bank its due, JD pays the supplier the remaining amount for the product, provided that the product was defect free.

The buyer's pivotal position in supply chain finance is of special interest, as it sheds light on the question of how to best deal with the supplier risk. A critical source of supplier risk that derives the contract and financing structure is supplier product reliability and defects. In many cases, a main reason for a large buyer to delay the payment to small suppliers is to make sure that the delivered products are not defective (see, e.g., Klapper [1]). This is because if a batch of delivered goods from a supplier is defective, often the products are returned and the supplier does not get paid. As a result a supplier can find itself in financial distress and may not be able to pay back to its creditors. This gets reflected on the loan interest rates since the creditors price the loans to cover the supply chain risk they would be assuming because of potential defects. The crux of the supplier financing structure problem lies at how this supply chain risk could be distributed more efficiently to lower financing costs, keep the wholesale price low and avoid under-production. One important question is whether buyer intermediation in supplier financing is effective in reducing costs and increasing supply chain efficiency. Further, how does the Buyer Intermediated Financing (BIF) compare to commercial loans that do not directly involve the buyer? In this paper, centered around these questions, we study the effectiveness of buyer intermediation in supplier finance.

2.2 Literature Review

Our work lies at the interface of operations and financial decisions, exploring financing in the supply chain when there are payment delays contractually agreed between the buyer and the supplier. As such, it is related to the trade credit literature, which studies such payment delays in the channel often employed to provide financial flexibility to buyers with capital limitations. Trade credit has been extensively studied in a stream of finance literature, exploring a broad range of topics including supplier size, product differentiation, and insurance and default premiums on trade credit contract terms (see Smith [2], Petersen and Rajan [3], Cunat [4], Giannetti et al. [5], Klapper et al. [6], and Murfin and Njoroge [7] among others). In the operations management literature, Xu and Birge [8] provide one of the early studies that captures the decision of a capital constrained buyer. They show that firm value can be significantly improved by integrating financial and operational decisions. Dada and Hu [9] show that in a Stackelberg game setting, a capital constrained newsvendor would borrow from bank but order an amount that is less than what would be optimal. Zhou and Groenevelt [10] investigate the case when a supplier provides subsidies to a budget constrained retailer. Caldentey and Chen [11], Kouvelis and Zhao [12] (Kouvelis and Zhao [13], Kouvelis and Zhao [12]) and Jing et al. [14] examine the interplay between a supplier, a budget constrained retailer and a bank, demonstrating that when bank loans are competitively priced, retailers will prefer supplier financing to bank financing if an optimally structured trade credit contract is offered, but when the bank has market power in setting the interest rate, either form of financing can be preferable depending on the market parameters.

Yang and Birge [15] show that even when bank financing and supplier financing can be used jointly, supplier financing is still preferred to bank financing. In addition, using firm-level data, they find that the financing pattern predicted by their model is used by a wide range of firms. Alan and Gaur [16] demonstrate that when a bank is a profit maximizer, the collateral value of inventory is a function of the bank's belief regarding the firm's demand distribution. Luo and Shang [17] explore the interaction between the inventory policy and trade-credit in multi-period setting, demonstrating that a simple myopic inventory policy based on a target stock level and the firm's working capital is optimal.

In contrast to many papers on trade credit cited above, our paper is centered on the financial constraints of suppliers rather than the buyers. Hence, the literature on reverse factoring is closely related to our paper as it also studies how a large retailer can collaborate with a bank to help supplier to obtain cheap financing by reallocating the financial flow. However, the buyer intermediated financing scheme we study in this paper has differences from the standard reverse factoring: First, in BIF, the buyer sets the interest rate rather than the bank. Second, it allows the supplier to choose the loan amount rather than having a preset payment schedule. Third, the scheme is mainly handled and operated by the buyer (e.g., JD) who manages supplier accounts on an ongoing bases. As such, key issues and the outcome of buyer intermediated financing also differ from that of reverse factoring. Studying Nestlé's implementation of reverse factoring in Russia, Corsten [18] notes that some suppliers resisted to participating in reverse factoring, because Nestlé demanded that a 30 day payment delay to be implemented, and because the suppliers did not feel familiar with the new procedure nor comfortable working with international banks. JD, on the other hand, did not have much resistance from its suppliers. A main reason for this was because JD's BIF scheme did not extend the existing payment delay. Further, the process was largely managed (intermediated) by JD, and the suppliers were working with domestic banks they knew, i.e., the unfamiliarity in the process for the suppliers was minimized.

Tanrisever et al. [19] study how reverse factoring creates value for each party in the supply chain and how the value is affected by the spread in exogenous financing costs determined by the bank, the working capital policy, the payment period extension and the risk free rate. They also explore the impact of reverse factoring on operational decisions using make-to-order and make-to-stock models. Van der Vliet et al. [20] study the effect of payment extension in reverse factoring using simulation-based optimization, finding that length of the payment period can get reflected on the supplier's financing cost in a nonlinear way. Rui and Lai [21] explore deferred payments to suppliers as a way to incentivize suppliers to invest in improving their product quality. They show that deferred payments can improve investments and compare its effectiveness to product inspections by the buyer. Wu et al. [22] explore buyer-backed supplier finance through a centralized two-stage stochastic programming model, finding that the buyer's guarantee in financing is necessary if the demand is large, supplier's capital is inadequate or the market finance interest rate is high. They also find that in this single decision-maker setting, the buyer can improve her payoff by guaranteeing the supplier's loan. In our paper, we study buyer intermediated financing in a three-way decentralized game between the supplier, the buyer and the bank with supplier defects and endogenous buyer determined interest rate and wholesale pricing. We compare the performance of two different financial schemes in this strategic setting with asymmetric information, as employed in practice by companies such as JD. We further identify the conditions, under which in equilibrium the buyer intermediated financing scheme can improve the buyer's payoff or reduce it, and apply the theoretical findings to data from JD to estimate unobservable parameters, test the theory, and measure efficiency.

Another stream of research related to our paper concerns supply chain risk and supply chain default. Tomlin [23] studies different types of disruption management strategies and shows that the nature of disruption such as length and uptime influences which strategy to choose. Babich [24] and Babich et al. [25] examine how default affects supplier competition and diversification. Dada et al. [26] show that in a supply chain where there are both reliable and unreliable suppliers, low production cost, rather than reliability, is still the most important criteria for choosing suppliers. Lai et al. [27] show that with financial constraints, a supply chain would maximize its efficiency by operating under a combination of consignment and pre-order modes. Swinney and Netessine [28] demonstrate that in the presence of default risk, long-term contracts are preferred over short term contracts. Yang et al. [29] examine how asymmetric information influences the value of risk mitigation strategy. They illustrate that information asymmetry will cause reliable suppliers to use back production option under default, and a manufacturer would be willing to pay for information when backup production cost is not very high. Babich [30] presents conditions under which, when facing a risky supplier, a downstream firm could make ordering decisions independent of subsidy decisions. Dong and Tomlin [31] examine how business interruption insurance, along with operational measures such as investing in inventory and using emergency sourcing, could help mitigate the disruption. They show that insurance and operations measures could be either substitutes or complements. In addition, a number of papers study operational and financial hedging as means of managing supply chain risk (see, e.g., Boyabatlı and Toktay [32], Gaur and Seshadri [33], Tomlin and Wang [34], Ding et al. [35], Li and Debo [36], Chod et al. [37], and Wang et al. [38] among others). We study a financing method that transfers risk among supply chain members in a novel way, and show that by allocating risk away from the supplier and towards the buyer, BIF can improve supply chain performance. Our study demonstrates that when suppliers are cash constrained, in certain cases buyers prefer assuming more risk to create liquidity in the supply chain.

2.3 Theory

In order to derive our hypotheses and provide the theoretical layout of our structural empirical analysis, we first present our game theoretical framework of the financing structures. We start with the general model description and then provide the details of the two financing models we study, namely the benchmark Commercial Loans and the Buyer Intermediated Financing model we are studying.

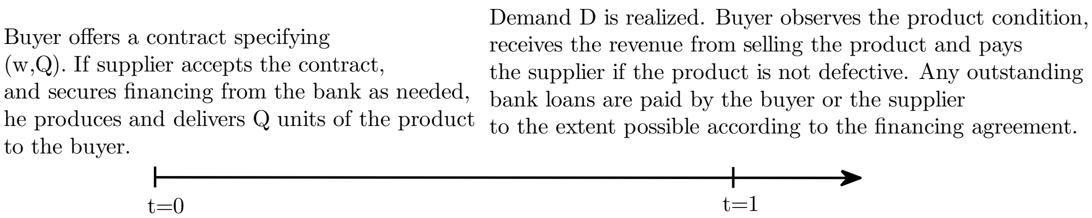

Figure 2.1: Sequence of events

2.3.1 Model Description and Sequence of Events

Consider a two-layer supply chain with a large downstream *retailer* (or *buyer*) and an upstream *supplier*, who is potentially budget constrained. That is, the supplier's initial capital can be insufficient to produce what is ordered. The funds the supplier may need to finance its operations can be provided by a third-party *bank*. The retailer is large enough that, independent of the revenue from selling the product, she can always cover a loan she has committed to pay.[1]

There are two time periods in the model, indexed as $t = 0$ and 1. At time $t = 0$, the retailer, who is at a dominant position within the supply chain, offers the supplier a contract, specified by the pair (w, Q), where w is the wholesale price, Q is the quantity ordered. The unit production cost for the supplier is c_p. If the supplier's budget at $t = 0$, denoted as B_0, is insufficient to cover the production costs c_pQ, the supplier also needs to secure financing to complete the production. Considering the offer and the financing needs and conditions (detailed below), the supplier may accept or decline the contract offer. If the offer is accepted, supplier produces the goods and delivers them to the buyer. At $t = 1$, the consumer demand, D realizes.

[1]For the rest of the paper, for convenience in exposition, we will refer the retailer as "she", the supplier as "he", and the bank as "it".

The retailer delivers the product to the consumers and receives the corresponding revenue at a unit price p. For each unit of unmet demand, the retailer incurs a goodwill loss cost of c_g. The consumer demand distribution has a c.d.f. $F(\cdot)$ and a p.d.f. $f(\cdot)$. Also for future reference, define $R = w \cdot D$ and denote its c.d.f. and the p.d.f. of by $F_R(\cdot)$ and $f_R(\cdot)$.

The supplier can be one of two types: low product defect with probability $\pi_l \in (0, 1)$ or high product defect with probability $1 - \pi_l$.[2] If he is the low product defect type, his product is defective with probability $a_l \in (0, 1)$. Otherwise his product is defective with probability $a_h > a_l$. Define η_a, as the ex-ante product defect probability for a given supplier, i.e., $\eta_a = \pi_l a_l + (1 - \pi_l)a_h$. After the product reaches the customers at time $t = 1$, it is revealed whether it is defective or good. If the product is defective, customers return the product to the retailer and the retailer returns all the units to the supplier. The retailer gets full refund for the defective products but it costs her c_e for each item returned from customers for processing. A customer may also return the product with probability a_n even when a certain product is not defective. In such a case, the buyer again incurs a processing cost of c_e per unit for the returned item, but since the product is good but considered as a used item, she cannot return it to the supplier for a refund. For simplicity, we assume that the salvage value for a returned undefective product for the buyer is

[2]This implies a separation between two supplier types and has an impact on their creditworthiness. As an example, JD separates its suppliers into two broad groups. The first group (labeled categories A, B, and C suppliers by JD) are considered higher quality suppliers who are more dependable, have low defect rate and consequently lower risk of going bankrupt, and hence deemed as more creditworthy. The second group (labeled D and E) are considered lower quality, high defect-rate-suppliers who are considered by JD as risky. JD chooses to offer supplier finance services only to those suppliers in categories A,B, and C, i.e., reliable suppliers with low expected defect rates.

zero.

Finally, the retailer sends all unsold products to the supplier for a full refund, w per unit. We assume that the expected revenue from selling the product exceeds the expected losses from exchange costs, i.e., $(1-a_l)((1-a_n)p - a_n c_e) - a_l c_e > 0$, since otherwise the product would not be viable for the supply chain with negative expected proceeds from each unit sold. The bank does not know the type of the supplier and hence the true defect rate of the product. The retailer on the other hand, has the history of the transactions with the supplier and knows the type of the supplier and the true defect rate. Figure 2.1 summarizes the general outline of the sequence of events.

2.3.2 Financing Alternatives

We next present the details of the two financing schemes we study individually. For simplicity in exposition, we will focus on the case where the retailer is low product defect type (i.e., the probability of defect for his product is a_l).[3]

2.3.2.1 Commercial Loan

We start with the case where the supplier borrows from a bank without the retailer being an intermediary. This is a traditional commercial loan scenario, which we denote by cl. The time line follows the general outline: The retailer makes the contract offer (w, Q) at $t = 0$. If the supplier's initial budget B_0 is not sufficient to

[3] This reflects JD's practice of underwriting financing of only higher quality suppliers as we mentioned above.

cover production, he needs to obtain a loan l at time $t = 0$ from the bank, payable due at $t = 1$. The interest rate for the bank loan is determined competitively, i.e., the bank makes no extra expected profit from the loan compared to what it would get from investing in the risk-free asset. Denote the risk-free rate by r_f and the bank's interest rate by r_{cl}. Also, for notational convenience, define $\rho = (1 + r_f)/(1 - \eta_a)$.

If the supplier accepts the offer and secures financing, he produces and delivers the goods at $t = 0$. The consumer demand and the retailer revenues materialize at $t = 1$, and if the product is not defective, the retailer makes the full payment to the supplier. If the product is defective however, the retailer returns all the products to the supplier and the supplier does not get paid. At the time the loan payment is due, he pays the bank the loan principal plus interest to the extent possible depending on his cash position. The supplier's cash position at $t = 1$ before paying the loan can then be written as

$$B_1 = \begin{cases} (B_0 + l - c_p Q)(1 + r_f) + w \min\{Q, D\} & \text{if the product is not defective}\,; \\ (B_0 + l - c_p Q)(1 + r_f) & \text{if the product is defective}\,. \end{cases} \tag{2.1}$$

Denote the supplier's expected end profit as a function of Q, w, and l under a commercial loan scenario as Π_s^{cl}. At $t = 1$, after it is revealed whether the product is defective or not, the supplier will pay the loan it borrowed from the bank to the extent possible, i.e., will make a payment of $\min\{l(1 + r_{cl}), B_1\}$ and hence will have an end profit $B_1 - \min\{l(1 + r_{cl}), B_1\} = (B_1 - l(1 + r_{cl}))^+$. Therefore, by (2.1) we have

$$
\begin{aligned}
\Pi_s^{cl}(Q,w,l) &= \mathbb{E}[(B_1 - l(1+r_{cl}))^+] \\
&= (1-a_l)\mathbb{E}[((B_0 + l - c_pQ)(1+r_f) + w\min\{Q,D\} - l(1+r_{cl}))^+] \\
&\qquad + a_l\mathbb{E}[((B_0 + l - c_pQ)(1+r_f) - l(1+r_{cl}))^+]. \qquad (2.2)
\end{aligned}
$$

The supplier has to make sure that he borrows enough to cover his production cost, while taking into account that the bank will set the interest rate competitively. The bank's competitive rate setting means that its expected payoff from lending to the supplier is the same as its payoff from investing the loan amount in the risk-free asset. Then, given the contract offer (w,Q), the supplier's problem if he accepts the offer can be written as

$$
\begin{aligned}
&\max_{l\geq 0} \Pi_s^{cl}(Q,w,l) \\
&\text{s.t.} \quad B_0 + l - c_pQ \geq 0, \ \textbf{(Supplier's production budget constraint)} \\
&\qquad l(1+r_f) = (1-\eta_a)\mathbb{E}[\min\{l(1+r_{cl}), (B_0 + l - c_pQ)(1+r_f) + w\min\{Q,D\}\}] \\
&\qquad\qquad + \eta_a\mathbb{E}[\min\{l(1+r_{cl}), (B_0 + l - c_pQ)(1+r_f)\}]. \\
&\qquad\qquad \textbf{(Bank's competitive interest setting equation)}
\end{aligned}
\qquad (2.3)
$$

Define the retailer's expected end profit as a function of Q and w for the commercial loan financing case as $\Pi_r^{cl}(Q,w)$. If the supplier's product is not defective (with probability $1-a_l$), the retailer collects a revenue p for each unit sold and unreturned by the customers (a fraction of $1-a_n$); loses c_e per unit in processing costs for each unit sold and returned by customers (a fraction of a_n); and pays w to the supplier per each unit sold (returning all unsold units to him). If the supplier's product turns out to be defective, on the other hand, the retailer does not get any revenues and returns all products to him without paying, while incurring a processing cost of c_e for each unit sold. In both cases, he incurs a goodwill loss of c_g per unit of unfulfilled demand. Hence, we have

$$\Pi_r^{cl}(Q,w) = \mathbb{E}[(1-a_l)((1-a_n)p-a_nc_e-w)\min\{Q,D\}-a_lc_e\min\{Q,D\}-c_g(D-Q)^+]. \tag{2.4}$$

The retailer has to ensure that the supplier's terminal cash position will be no less than what he would otherwise obtain by investing his money on the risk free asset (Individual Rationality or **IR**) when the supplier chooses the optimal loan, L, for a given contract offer (under Incentive Compatibility of the supplier's choice or **IC**). Hence the retailer's problem when the supplier financing is obtained through a commercial loan can be written as

$$\begin{aligned}
&\max_{Q,w\geq 0} \Pi_r^{cl}(Q,w)\\
&\text{s.t.} \quad \Pi_s^{cl}(Q,w,L) \geq B_0(1+r_f), \ \textbf{(IR)}\\
&\text{where } L \text{ solves the supplier's optimization problem for } (Q,w) \text{ as given in (2.3).} \ \textbf{(IC)}
\end{aligned} \tag{2.5}$$

2.3.2.2 Buyer Intermediated Financing

Traditional commercial loans, though being able to provide suppliers with some liquidity, still make them face banks or loan companies as borrowers. This may be especially a problem for small suppliers or new businesses who have little or no credit history. In Buyer Intermediated Financing (BIF), however, a larger retailer can help small suppliers get better financing by intermediating between them and a bank, and effectively underwriting the suppliers' loan back payment. We denote the BIF financing case by bi.

The timeline of the BIF approach is as follows: At $t = 0$ the supplier and the retailer agree on the contract, the supplier can obtain a loan from the bank to cover his costs *arranged* by the retailer: The retailer works together with the supplier and the bank to get a loan at a discount percentage $\delta_{bi} = 1 - 1/(1 + r_{bi}) \in (0, 1)$ set by the retailer herself, where r_{bi} is the equivalent interest rate. In return, the retailer commits to paying back the loan. In particular, for $0 \leq l \leq wQ$, the supplier obtains $l(1 - \delta_{bi})$ at $t = 1$ and the retailer agrees to pay l back to the bank at $t = 1$ after the goods are sold and the revenue is received. At that time, if the product is not defective, the retailer pays the supplier the remainder of the account $wQ - l$. If the product is defective, however, the retailer just pays the loan due amount l back to the bank and does not pay the remaining due to the supplier as all the products are returned to the supplier. In both cases, all unsold products are returned to the supplier for a full refund of w per unit.

One important thing to note here is that, as we described above, BIF exposes the retailer to an additional risk, covering the supplier's loan payment when the product is defective. Because of this, the retailer has incentives to limit the loan amount the supplier borrows. Further, if a supplier borrows beyond what is sufficient to cover his production costs, i.e., if $l(1-\delta_{bi}) > (c_pQ - B_0)^+$, then he will be investing it in an outside option, such as the risk-free asset, without benefiting the retailer's operations and exposing her to unnecessary extra risk. Therefore, in order to prevent such exploitation of the financing program, the retailer chooses the contract parameters to eliminate incentives to borrow more than necessary to produce, i.e., she aims to ensure that $l(1-\delta_{bi}) \leq (c_pQ - B_0)^+$.

Denote the supplier's expected end profit in this case by Π_s^{bi}. At $t = 0$, after the products are delivered, the supplier will have obtained $l(1-\delta_{bi})$ from the bank and paid c_pQ in production costs. Hence he will have a starting cash position of $B_0 + l(1-\delta_{bi}) - c_pQ$ at $t = 1$. If the product is not defective, the supplier will be paid wQ for the sold products minus the loan amount l and the refunds for the unsold products, i.e., $wQ - l - w(Q-D)^+ = w\min\{Q, D\} - l$. If the product is defective, the supplier does not get paid further. Given the contract and loan parameters, Q, w, δ_{bi}, the supplier maximizes Π_s^{bi} while making sure to have enough cash at $t = 0$ to cover his production costs, i.e., have non-negative production budget. Then, the supplier's problem can be written as

$$\max_{0\le l\le wQ} \Pi_s^{bi}(Q,w,\delta_{bi},l) = \max_{0\le l\le wQ} \{(B_0 + l(1-\delta_{bi}) - c_pQ)(1+r_f) + (1-a_l)(w\mathbb{E}[\min\{Q,D\}] - l)\} \quad (2.6)$$

$$\text{s.t.} \quad B_0 + l(1-\delta_{bi}) - c_pQ \ge 0.$$

(Supplier's production budget constraint)

The retailer's payoffs in the BIF case are the same as described in Section 2.3.2.1 with one modification: The retailer pays the loan amount back to the bank when it is due, whether the product is defective or not. That is, when the product is defective, the retailer has an additional payment of l she commits to make. Therefore for the discount percentage $\delta_{bi} \in (0,1)$, and when the suppliers borrows l, the retailer's expected profit for the BIF case is $\Pi_r^{bi}(Q,w,\delta_{bi}) = \Pi_r^{cl}(Q,w) - a_l l$, where $\Pi_r^{cl}(Q,w)$ is as defined in (2.4).

The retailer again has to ensure that the supplier is not worse off than investing his money on the risk free asset (**IR**), and that the supplier chooses the optimal loan, L, for a given contract offer (**IC**). Further, as we described above, the retailer has to make sure that the supplier does not borrow more than he needs to cover the production costs, and that the bank is not making a loss by lending money in the

BIF scheme. Then the retailer's problem under the BIF policy can be written as

$$
\begin{aligned}
\max_{Q,w\geq 0,\, \delta_{bi}\in(0,1)} \Pi_r^{bi}(Q,w,\delta_{bi}) \quad &= \Pi_r^{cl}(Q,w) - a_l L \\
\text{s.t.} \quad & \Pi_s^{bi}(Q,w,\delta_{bi},L) \geq B_0(1+r_f),\ \textbf{(IR)} \\
& (1+r_f)(1-\delta_{bi}) \leq 1, \\
& \textbf{(The bank's non-negative profit constraint)} \\
& L(1-\delta_{bi}) \leq (c_pQ - B_0)^+,\ \textbf{(The constraint to limit} \\
& \qquad\qquad \textbf{supplier overborrowing)} \\
& \text{and where } L \text{ solves the supplier's optimization problem} \\
& \text{for } (Q,w,\delta_{bi}) \text{ as given in (2.6). } (\textbf{IC})
\end{aligned}
\tag{2.7}
$$

Figure 2.2 depicts a comparison of the two financing schemes. As shown in panel (a), when financing through a commercial loan, the loan transaction is fully between the supplier and the bank. Any risk of non-payment of the loan back to the bank is carried by the bank. For the Buyer Intermediated Financing scheme, on the other hand, the buyer sets the interest rate on the loan the supplier is receiving at $t = 0$ as shown in panel (b), and commits to pay back the loan with interest at $t = 1$ to the bank. Table A.1 in the online supplement summarizes our model notation.

2.3.2.3 The First Best Solution

Lastly, we present the formulation of the supply chain ideal benchmark, i.e., the first-best case, where the supply chain is integrated and the decisions are centralized. In this case, the supplier's budget constraint as well as the participation

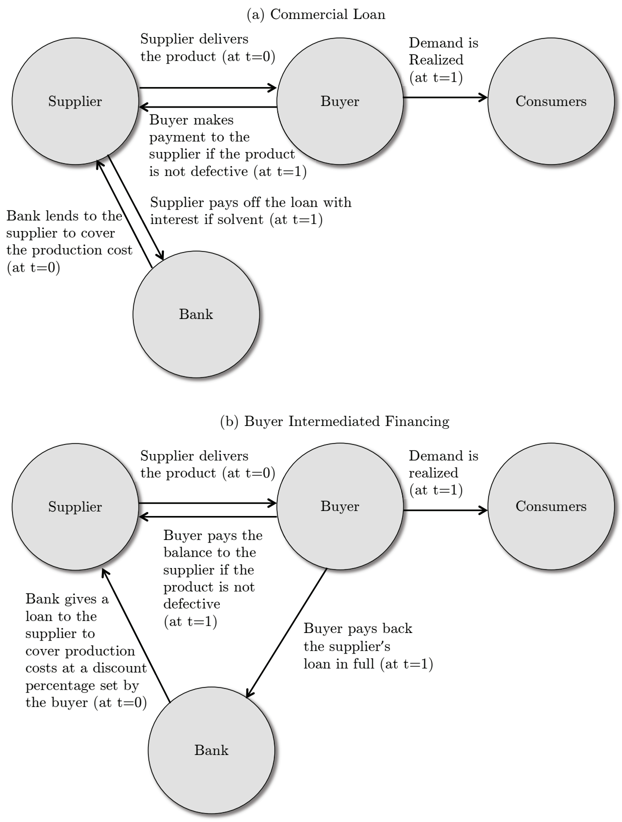

Figure 2.2: Comparison of the two financing schemes. Panel (a) shows the transaction structure for financing through a Commercial Loan and panel (b) through Buyer Intermediated Financing.

and incentive compatibility constraints no longer enter the formulation. The first best problem, which we denote by fb, then can be formulated as

$$\max_{Q\geq 0} \Pi_{fb} = \max_{Q\geq 0} \quad \{ \mathbb{E}[((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e) \min\{Q, D\} \\ -c_g(D-Q)^+ - c_p Q(1+r_f) + B_0(1+r_f)] \}. \tag{2.8}$$

Solving (3.11), the optimal order quantity for the first best case can be found as

$$Q^*_{fb} = F^{-1}\left(1 - \frac{c_p(1+r_f)}{(1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g}\right). \tag{2.9}$$

Plugging (3.12) back in (3.11), we can obtain the first-best channel profit Π^*_{fb}. Throughout the rest of the paper, we will be using the first-best quantity Q^*_{fb} and surplus Π^*_{fb} as our benchmarks for quantity and supply chain surplus under full efficiency.

2.3.3 Discussion of Model Assumptions and Elements

Before we start the analysis of the model, let us first discuss our model elements. Since we will be using structural estimation based on our model on data from JD, we want to include all factors that are considered important by JD managers in the model. To this end, we have had detailed interviews with JD managers as well as studying the company's financial statements and other publicly available information. From our interviews, a few observations came out strongly. First, JD's managers are quite concerned about not having unmet demand. They worry that a customer who cannot find the product she is looking for at the platform can turn sour of the channel, which translates into lost future demand. Therefore, the managers put weight into meeting the demand and minimizing goodwill loss. As a result, we include unit goodwill loss as a factor to be estimated in the model (c_g). Second, managers as well as the upper level executives were keeping an eye on the operational expenses such as costs of handling defective products and customer returns on non-defective products, as well as keeping the process costs low. The considerations for these costs may end up shifting the orders, and hence, we included these factors (such as the customer return probability of non-defective goods a_n and unit return processing costs c_e) in our model as well.

We consider all-or-none type defects or product problems instead of defects on part of the products in the delivery. In addition to providing simplicity to the model, this also captures the gist of a core issue: all-or-none type defects are the systematic type of defects that the buyers like JD are concerned about most when they are signing contracts, and setting financing structures. This kind of defects (similar to car recalls for instance) are the ones that are likely to cause a small supplier not be able to make their loan payments and default. Compared to the frequency and impact of the all-or-none type defects, the impact of several products in the entire batch being broken or defective is much smaller and such cases are not central to the questions we examine. Hence, we focus on the former defect type and, for tractability and model simplicity we do not model the latter.

In our model, the buyer sets the wholesale price and the order quantity in the contract. This reflects the common contract procedure for many large buyers, including JD. Such retailers tend to have significant bargaining power, especially over their small suppliers, and set the wholesale price and quantity for the contracts they engage in. Naturally, they set the wholesale price high enough to make sure that the supplier still accepts the contract (as can be seen in the problem formulations in Section 3.3.1). In addition, JD can return all unsold products, even if the products were good, back to the supplier and get reimbursed at the full wholesale price, w. This is again a common return policy employed by many large retailers due to their strong bargaining power and the fact that they provide a visible popular outlet to the suppliers to reach a broad consumer population. Our model is set up to include this industrial practice and enable our structural estimation to capture the nature of JD's contract structure.

We assume that the buyer's salvage value for non-defective products returned from the customers is zero. In addition to providing model simplicity, this also reflects the reality of the industry practice, as indicated from our interviews with JD's managers, since returned products are considered used and usually either discarded or given away for free or at high discounts, and salvaging them is not a systematic cash flow stream for the buyer.

Finally, one thing in the buyer's BIF optimization problem (2.7) that needs to be highlighted is the determination of the discount percentage, δ_{bi}, and its relation to the constraint that limits supplier over-borrowing. The buyer in a very targeted way, sets the discount percentage to discourage the suppliers from borrowing more than they need to cover their production costs, c_pQ, to satisfy the constraint. Notice that when the supplier's initial budget, B_0 is less than the production costs, c_pQ, the constraint to limit supplier borrowing in (2.7) together with the supplier's production budget constraint in (2.6) implies $L(1-\delta_{bi}) = c_pQ - B_0$, i.e., the supplier borrows exactly the amount he needs to cover the production costs. The retailer's lever to ensure this is δ_{bi}. In fact, what makes sure that the supplier does not borrow more than he needs is the interaction between the supplier's objective function and the constraint to limit supplier borrowing (see our discussion of Proposition 3 and its proof in the online supplement). It is important to note that our formulation in (2.7) reflects JD's decision process for setting the discount percentage in practice and is essential for determining the discount percentage for the empirical analysis in Section 2.4 that uses JD's data.

2.3.4 Equilibrium Analysis

In this section, we provide the equilibrium solutions and comparisons of the two financing methods we described above. We start with the equilibrium outcome for the case when the supplier's initial budget position is relatively high.

Proposition 1 *Define*

$$\bar{Q}_{cl} = F^{-1}\left(1 - \frac{c_p(1-a_l)(1+r_f)}{(1-\eta_a)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right), \quad (2.10)$$

$$\bar{Q}_{bi} = F^{-1}\left(1 - \frac{c_p(1+r_f)}{(1-a_l)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right). \quad (2.11)$$

For $\varphi \in \{cl, bi\}$, $Q^*_{fb} > \bar{Q}_\varphi$. In each financing method φ, if $B_0 \geq c_p\bar{Q}_\varphi$ then the supplier obtains no loan in equilibrium. Further, (i) if $B_0 \geq c_p Q^*_{fb}$, then the equilibrium order quantity is $Q^*_\varphi = Q^*_{fb}$, (ii) otherwise $Q^*_\varphi = B_0/c_p$. In each case, the equilibrium wholesale price is

$$w^*_\varphi = \frac{c_p Q^*_\varphi(1+r_f)}{(1-a_l)(Q^*_\varphi - \mathbb{E}[(Q^*_\varphi - D)^+])}. \quad (2.12)$$

Proposition 1 states that, when the supplier's budget level is sufficiently high, in both financing schemes we study, he will not need to borrow to produce, and instead he will pay for his operations using his own funds. Further, as stated in part (i), if the supplier's budget is sufficiently high to produce the first-best quantity, he produces at that level using his own funds. The financing costs that are paid to the third-party bank as well as the misalignment from decentralized decision of the supplier choosing his loan amount disappear and the supply chain gets coordinated. As indicated in part (ii), if the supplier's budget is insufficient to produce the first-best quantity but still not too low, in the optimal contract, he still will use his own funds. However, in this case, the retailer sets the wholesale price that makes the supplier break even and orders a quantity less than the first-best (notice that in this case $Q^*_\varphi = B_0(1 + r_f)/c_p < Q^*_{fb}$). Consequently the equilibrium outcome will be strictly worse than the first-best outcome. That is, for an intermediate supplier budget band, the supply chain will operate without financing from a third-party entity but without full efficiency.

On the other hand, when the supplier's budget is not sufficiently high, he will need to obtain financing. We study this case under each financing scheme next. Note that henceforth, we will be using the quantity thresholds defined in (2.10)-(2.11) in our notation. We start with the case of financing through a commercial loan. When analyzing the commercial loan we focus on equilibria that avoids trivial investment behavior. Specifically, in certain cases, the supplier can borrow from the bank just to reinvest in the risk-free asset without affecting any equilibrium payoffs or the equilibrium outcome other than the loan amount and the interest rate. The supplier in fact would be indifferent to take such an action and would have no reason or incentive to undertake it over borrowing the necessary amount.[4] We would like to focus on the equilibrium outcomes that do not include such trivial supplier reinvestment, which is presented in the following proposition.

[4]Please see the Proof of Proposition 2 for details.

Proposition 2 *For commercial loan financing, if $B_0 < c_p\bar{Q}_{cl}$, then in the unique equilibrium where the supplier does not borrow an excess amount to reinvest,*

$$
\begin{aligned}
Q_{cl}^* &= \bar{Q}_{cl}, && (2.13)\\
w_{cl}^* &= \frac{c_p Q_{cl}^* \frac{(1+r_f)}{1-\eta_a} - B_0(1+r_f)(\frac{1}{1-\eta_a} - \frac{1}{1-a_l})}{Q_{cl}^* - \mathbb{E}[(Q_{cl}^* - D)^+]}, && (2.14)\\
L_{cl}^* &= c_p Q_{cl}^* - B_0\,, && (2.15)
\end{aligned}
$$

and $r_{cl}^* > r_f$ is the unique solution for r_{cl} to the equation

$$\rho L_{cl}^* = \int_0^{L_{cl}^*(1+r_{cl})} z f_R(z)dz + L_{cl}^*(1+r_{cl})(1 - F_R\left(L_{cl}^*(1+r_{cl})\right))\,. \qquad (2.16)$$

As Proposition 2 states, when the supplier's budget is sufficiently low, it becomes optimal for the retailer to offer a contract that induces the supplier to borrow to support increased production. Given the loan amount requested by the supplier, the bank will set the interest rate (r_{cl}^*) competitively as given in the rate-setting equation in (2.3), which algebraically translates into (2.16) as stated in the proposition. As we mentioned above, focusing on equilibria that exclude trivial reinvestment behavior, in the predicted outcome, the supplier will borrow the amount needed to exactly cover his production costs at $t = 0$, i.e., the supplier's production budget constraint in (2.3) is binding. Further, in order to maximize profits, the retailer sets the wholesale price to make the supplier's IR constraint in (3.10) also binding. The equilibrium order quantity, Q_{cl}^* is then found by optimizing the retailer profits under these conditions.

Next, we present the equilibrium outcome for the Buyer Intermediated Financing (BIF) scheme.

Proposition 3 *For buyer intermediated financing, if $B_0 < c_p\bar{Q}_{bi}$, then in equilibrium, the supplier borrows up to the level to cover his production costs. Further,*

$$\begin{aligned}
\delta_{bi}^* &= 1 - \frac{1-a_l}{1+r_f}, && (2.17)\\
Q_{bi}^* &= \bar{Q}_{bi}, && (2.18)\\
w_{bi}^* &= \frac{c_p Q_{bi}^*(1+r_f)}{(1-a_l)(Q_{bi}^* - \mathbb{E}[(Q_{bi}^* - D)^+])}, && (2.19)\\
L_{bi}^* &= (c_p Q_{bi}^* - B_0)\,\frac{1+r_f}{1-a_l}\,. && (2.20)
\end{aligned}$$

Note that for any $\delta_{bi} \geq 0$, the corresponding interest rate for the buyer intermediated financing scheme is $r_{bi} = 1/(1-\delta_{bi}) - 1$. Hence, by Proposition 3, $r_{bi} = 1/(1-\delta_{bi}) - 1 = (1+r_f)/(1-a_l) - 1 > r_f$. That is, unlike the commercial loan, under the BIF structure the bank makes strictly positive profits. Yet, the retailer still chooses this rate in its three-way contract with the bank and the supplier, because the high interest rate restrains the supplier from borrowing more than he needs to cover the production costs, curbing the retailer's downside risk. As a result the supplier borrows only up to the amount he needs to cover his production costs, i.e., the retailer's target supplier loan amount. As such, the production budget constraint of the supplier in his optimization problem (2.6) is again binding. In addition, just as in the Commercial Loan case, in the optimal solution, the retailer maximizes profit by setting the wholesale price to make the IR constraint of the supplier in (2.7) bind

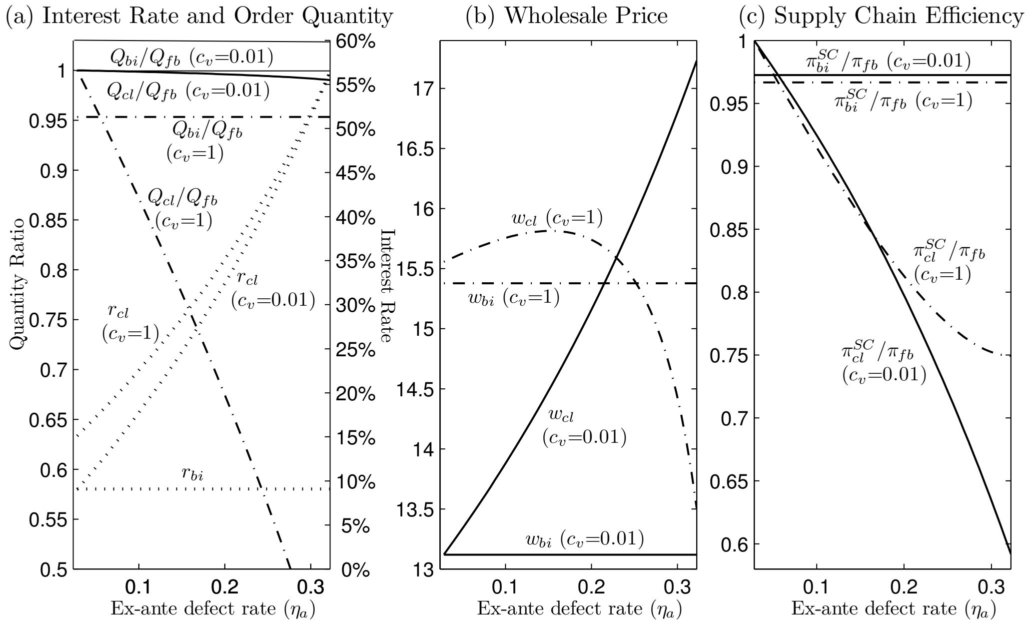

Figure 2.3: Comparison of the equilibrium outcomes for financing through Commercial Loans and BIF. Panel (a) illustrates the order quantity ratio with respect to first best as well as the interest rate for each financing scheme; panel (b) illustrates wholesale prices; and panel (c) shows the supply chain efficiency for varying ex-ante product defect rate (η_a). For all panels, the parameter values are a_l=0.03, c_p=12, p=20, c_g=1, c_e=0.2, a_n=0.015, B_0=5, r_f=0.06, the demand follows a log-normal distribution with log-mean $\mu = 0.5$. c_v refers to the Coefficient of Variation for the logarithm of the demand distribution, σ/μ, where σ is the log-standard deviation of the demand distribution.

as well.

We can now compare the outcomes of the two financing schemes in performance and efficiency. For simplicity in exposition, we will only focus on the case where $L^*_{cl}, L^*_{bi} > 0$.

Proposition 4

(i) Buyer intermediated financing has a lower interest rate than the commercial loan, i.e., $r_f < r^*_{bi} < r^*_{cl}$.

(ii) There exists a $\kappa > 0$ *such that if* $Var[D] < \kappa$, *then* $w^*_{bi} < w^*_{cl}$.

(iii) $Q_{bi}^* > Q_{cl}^*$, $\Pi_{bi}^{r*} > \Pi_{cl}^{r*}$, *and the supplier borrows a higher percentage of his production costs if and only if* $\eta_a > 1 - (1 - a_l)^2$.

Figure 2.3 demonstrates the comparison of the outcomes of the traditional commercial loan and the BIF cases. As part (i) of Proposition 4 states, BIF can reduce the effective interest rate, i.e., reduce the costliness of the loan. In fact, as can be seen from panel (a) of Figure 2.3, commercial loan interest rate increases sharply as the supplier's ex-ante defect rate (η_a) increases. As also stated in part (iii) of Proposition 4, when the ex-ante defect rate (η_a) is sufficiently low, the order quantity under the commercial loan is higher than that under BIF. This is because, even though BIF reduces the interest rate the supplier faces, it makes the retailer assume *increased risk*, since the retailer commits to cover the supplier's loan payment even when the product is defective and the supplier is unable to pay back the loan. This added risk reduces the retailer's incentive to order under BIF. However, as η_a becomes larger, because of the rising commercial loan interest rate, the order quantity under the commercial loan can sharply plunge and the order quantity under BIF can be significantly higher.

The wholesale price with BIF, on the other hand, can be lower or higher than the commercial loan. As can be seen in panel (b) of Figure 2.3, when demand variability is high (when the coefficient of variation for the log-demand, c_v, is 1), for low values of ex-ante riskiness of the loan η_a, BIF reduces the wholesale price since it reduces the cost of borrowing. However, when η_a increases, the commercial loan interest rate increases and the order quantity decreases significantly. Then the supplier needs to borrow little, which means that the higher bank interest rate under commercial loan does not inflate the required supplier compensation much. Consequently, the wholesale price can be lower with a commercial loan than BIF as can be seen in the figure. However, when the demand variability is sufficiently low, then the order quantity reduction caused by increased ex-ante supplier riskiness is low (as can be seen in Figure 2.3(a) for $c_v = 0.01$) and the supplier still needs to borrow a relatively large amount. As a result, since the interest rate under BIF is lower, the required supplier compensation and the wholesale price can be significantly lower compared to the traditional commercial loan as stated in part (ii) of Proposition (4), and as can also be seen in panel (b) of Figure 2.3 for the case of $c_v = 0.01$.

Increased supplier ex-ante risk level means sharply decreasing profits for the supply chain for the commercial loan case and the channel performance becomes better with BIF for high η_a levels, as stated in part (iii) of Proposition 4. Although, the supply chain profit is higher with a commercial loan for low η_a values, the efficiency gains with BIF can quickly reach 20% or more as the ex-ante defect rate increases as can be seen in panel (c) of Figure 2.3. Note that the supplier, has his participation (IR) constraint binding for both the commercial loan and the BIF schemes. Therefore the supplier, on average, is indifferent between traditional financing and BIF. However, as it is common in contracting models, it is in the stronger party's (the buyer's in this case) hands to decide to switch to the new method and ensure participation from the weaker party (the supplier) by sharing the gains in the supply chain surplus with him. So the key for the new BIF scheme to be incentive compatible for both the supplier and the buyer with respect to traditional financing is increased total supply chain surplus. From this perspective, part (iii) of Proposition 4 suggests that the BIF scheme is more likely be implemented when the supplier's ex-ante riskiness (η_a) is higher.

We will be using our theoretical results from this section in the rest of the paper in our empirical analysis in order to make structural parameter estimations, to derive and test hypotheses, and to perform efficiency and savings calculations.

2.4 Empirical Analysis

Utilizing the theoretical foundations we have laid out in Section 3.3, we now present our empirical results. Our data comes from JD, the largest Chinese online retailer (JD.com). JD employs a buyer intermediated financing scheme, which it launched at the end of 2012, and the service was adopted by a wide range of suppliers during the year of 2013. In 2013 the company has helped its suppliers get about One Billion Chinese Yuan (approximately \$167 Million) financing.[5] In this section, we test our theory by using data from this initiative.

2.4.1 Data description and Overview of the Empirical Strategy

The data consists of 9228 SKUs that are sourced from 170 different suppliers of JD. Among these suppliers, 114 of them have used the buyer intermediated finance service provided by the retailer (the *BIF* group), 43 of them were randomly

[5]For the rest of the paper, all currency figures will be given in Chinese Yuan unless indicated otherwise.

selected among suppliers who were eligible for BIF but chose not to use it (*Control Group 1*), and the remaining 13 suppliers were *not offered* to take part in BIF by JD (*Control Group 2*). The three groups correspond to 7474, 1388, and 366 SKUs respectively. The data, which is collected from January 1, 2012 to December 31, 2013, contains information on both the procurement and retail sides. The procurement data includes product name, wholesale price, annual order quantity, as well as the supplier identification. The retail data includes the retail price and the annual realized demand. In addition to the procurement and retail data, we also have data from the finance service, which contains each supplier's reliability rating evaluated by the retailer. Furthermore, for those suppliers who have used the supplier finance program, the data includes account receivables and the amount borrowed through the supplier finance service.

Our goal is to test the effectiveness and efficiency of BIF on a number of measures utilizing our theoretical foundation derived in Section 3.3. In order to perform these tests and measurements, we will use the structural equilibrium expressions of our model that use the demand distributions. Therefore, we first need to estimate the demand distribution for each SKU. In particular, we use a log-log price-quantity industry demand curve, and using quantity and realized sales data for each SKU we estimate the parameters of the demand curve for each industry. One thing to note here is that since the sales cannot exceed the available units, the sales data is censored to be the minimum of the order quantity and the demand, i.e., $\min\{Q, D\}$. In order to correct for this and recover the estimation for the true demand we use an Expectation-Maximization regression approach that achieves distributional estimation conditional on the observed sales (see, e.g., Dempster et al. [39], Aitkin and Wilson [40]). From this procedure, we obtain the estimated demand distribution for each SKU. Using these estimated demand distributions and the structural equilibrium expressions from our theoretical model, we then carry out a nonlinear least squares estimation to obtain the unobservable model parameters, namely, the average good will loss, the interest rate for each supplier who got a commercial loan in 2012, and industry demand forecast errors. Further details of the estimation procedures are given in Section 2.4.2.

Having obtained estimates for all our model parameters, we then perform direct and "difference-in-differences" tests on performance measures such as financing costs, wholesale prices, order quantities, and loan amounts before and after the BIF implementation, in order to test the predictions of the theory and the effect of BIF on the outcome. For these tests, we use the estimates on loan amounts, interest rates and forecast errors coming from equilibrium expressions of our theoretical analysis and the structural parameter estimation. Finally, calibrating our model with our estimation results, we analyze counterfactual scenarios of not employing BIF in 2013. We calculate expected supply chain surplus under the realized (BIF) and the counterfactual scenarios, and comparing the two, we estimate the percentage and monetary effects of utilizing BIF on channel profits. The tests on contract characteristics are given in Section 2.4.3, and the efficiency analysis is given in Section 2.4.4.

2.4.2 Estimation

2.4.2.1 Demand Estimation

We start by estimating the demand pattern for each industry. We use a log-log demand estimation model

$$\log(D_{ij}) = a_j + b_j \log(p_{ij}) + \epsilon_{ij}, \tag{2.21}$$

where D_{ij} is the demand for SKU i in industry segment j, p_{ij} is the price for that SKU, a_j is the industry-specific fixed-effect for demand, b_j is the industry-specific price elasticity, and ϵ_{ij} is the corresponding error term.

Assuming log-normality for demand (see, e.g., Olivares et al. [41] and He et al. [42]), define $\theta_j = (a_j, b_j, \sigma_j^2)$ as the parameter vector to be estimated for industry j, where σ_j^2 is the variance of the error terms in (2.21). Since the demand data only reveals the realized sales, censored in the sense that unmet demand is lost and unobserved, the estimation needs to be appropriately adjusted. To this end, we employ an Expectation Maximization (EM) iterative regression method to account for the unobserved component of demand. Without loss of generality, let n_j be the sample size for industry segment j, in which the first m_j demand entries are not binding with the respective order quantity and the rest $n_j - m_j$ demand entries are binding. Further, let D_{ij} denote the real demand, and let $D_{obs(ij)}$ denote the observed demand documented in the data. Note that for each industry segment j and for $1 \leq i \leq m_j$, $D_{ij} = D_{obs(ij)}$ will hold. Then for each industry j, and any given parameter vectors θ_j and θ', define the conditional log-likelihood function

$$\mathcal{L}(\theta_j;\theta',D_{ij}) = -\frac{n_j}{2}\log(2\pi\sigma_j^2) - \frac{1}{2}\sum_{i=1}^{m_j}\frac{(\log(D_{ij})-(a_j+b_j\log(p_{ij})))^2}{\sigma_j^2} - \frac{1}{2}\sum_{i=m_j+1}^{n_j}\frac{(\mathbb{E}[\log(D_{ij})|\theta',D_{obs(ij)}]-(a_j+b_j\log(p_{ij})))^2}{\sigma_j^2}. \quad (2.22)$$

The estimation starts with initial value θ_j^0, for each iteration k with parameter vector θ_j^k, proceeds by finding $\theta_j^{(k+1)}$ such that

$$\theta_j^{(k+1)} = \arg\max_{\theta} \mathcal{L}(\theta;\theta_j^k,D_{ij})\,, \quad (2.23)$$

replacing θ_j^k with θ_j^{k+1}, and continuing until convergence. A detailed derivation of the distribution parameter update equations are given in Section A.4 in the Online Supplement. The estimation results are presented in Table 2.1. Notice that all industry categories have downward sloping demand curves except for ceramics and coffee (in 2013). In addition to the relatively small number of data points for these two categories, the high experience-good characteristics of these two product types may be leading to increased demand for higher priced products in certain cases. However, the dominant downward sloping characteristic of the industry demand curves is demonstrated in the data as can be seen in the table.

The estimated parameters a_j^*, b_j^* together with σ_j^{*2} rendered by the regression iterations at convergence allow us to calculate the estimated demand distributions. The mean of the logarithm of uncensored demand for each SKU is calculated as $\mu_{ij}^* = a_j^* + b_j^*\log(p_{ij})$. To facilitate the use of individual SKU demand variance, we

Table 2.1: EM Estimation Outcomes for Demand Distributions

	2012			2013		
	a_j^*	b_j^*	σ_j^*	a_j^*	b_j^*	σ_j^*
Auto parts	7.9349***	-0.6520***	1.8928***	8.1646***	-0.9090***	2.0702***
	(0.2618)	(0.0579)	(0.2428)	(0.2115)	(0.0447)	(0.2213)
Baby and Pregnancy products	7.7621***	-0.6521***	2.1847***	6.5174***	-0.6544***	2.5661***
	(0.4246)	(0.1020)	(0.2041)	(0.5303)	(0.1290)	(0.1578)
Ceramics	3.8636***	0.1442	1.4420*	2.2376*	0.5161*	1.4629*
	(0.9110)	(0.2029)	(0.6510)	(1.2037)	(0.2984)	(0.5753)
Clothing	5.0869***	-0.5088***	1.4337***	5.8719***	-0.6452***	1.3255***
	(0.1038)	(0.0150)	(0.2277)	(0.0778)	(0.0116)	(0.2692)
Coffee	9.8742***	-0.6948*	2.2351***	2.4488***	0.3736***	1.2009***
	(1.2501)	(0.2729)	(0.2811)	(0.5162)	(0.1260)	(0.1756)
Computer accessories	6.0486***	-0.2573***	2.4155***	7.0620***	-0.3668***	2.0488***
	(0.3506)	(0.0696)	(0.1688)	(0.2763)	(0.0542)	(0.0952)
Cosmetics	10.5626***	-1.2404***	2.1028***	9.0997***	-1.0312***	2.1660***
	(0.2279)	(0.0461)	(0.1501)	(0.3809)	(0.0538)	(0.1289)
Electronic products	7.7538***	-0.6099***	2.3711***	6.4379***	-0.4528***	2.3238***
	(0.1033)	(0.0172)	(0.1383)	(0.1079)	(0.0192)	(0.1426)
Home improvement	7.6960***	-0.6123**	1.9522***	6.4461***	-0.4291***	1.8307***
	(1.2782)	(0.2299)	(0.0801)	(0.4346)	(0.0856)	(0.0892)
Household appliances	4.8624***	-0.0279	1.9786***	4.9783***	-0.1292**	2.2403***
	(0.2098)	(0.0445)	(0.0957)	(0.3012)	(0.0596)	(0.1066)
Sporting goods	5.5446***	-0.5508***	1.8918***	4.1401***	-0.3197***	1.9127***
	(0.2569)	(0.0495)	(0.1534)	(0.2296)	(0.0422)	(0.1132)
Staple goods	7.7621***	-0.4901***	2.2757***	8.7176***	-0.8694***	2.4912***
	(0.1987)	(0.0410)	(0.0712)	(0.2120)	(0.0434)	(0.1058)
Wine	7.8873***	-0.7627***	1.9292***	6.9250***	-0.4957***	2.0634***
	(0.6680)	(0.1296)	(0.1506)	(0.4211)	(0.0823)	(0.1741)

p<0.01 ***, p<0.05 **, p<0.1 *. Numbers in brackets are the corresponding standard errors for the parameters.

assume that the demand variance for each SKU is proportional to the mean of the logarithm of uncensored demand, i.e., $\sigma_{ij}^{*2} = \sigma_j^{*2}(\mu_{ij}/(\sum_{s=1}^{n_j} \mu_{sj}))$.[6] The logarithm of the uncensored demand for SKU i in industry segment j therefore follows $\log(D_{ij}) \sim \mathcal{N}(\mu_{ij}^*, \sigma_{ij}^{*2})$, i.e., each SKU has its distinct demand distribution.

Finally, to verify the consistency of our log-normality assumption, we check the normality tests on the errors from the fitted demand curves. In 25 out of the 26 industry segment demand curves calculated for 2012 and 2013, corresponding to 99.10% of the SKU observations, Pearson Chi-square normality tests on the residuals from regression specified by (2.21) indicate that the normality of the residual

[6]This is consistent with the commonly used Geometric Brownian Motion demand evolution model. See, e.g., Whitt [43] and Cadenillas et al. [44] among others.

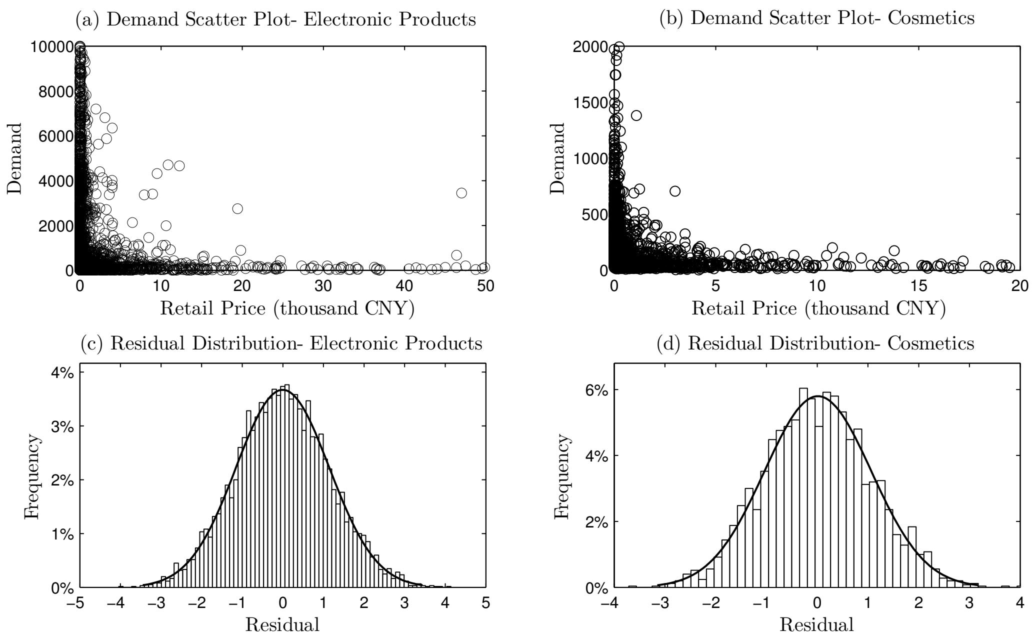

Figure 2.4: Two industry segment examples for the shapes of demand-price relationships, and residual distributions. Panels (a) and (b) demonstrate the demand-price scatter plots for Electronic Products and Cosmetics industry segments. The prices are given in thousand Chinese Yuans (CNY). Panels (c) and (d) exhibit the histograms for the residuals of the demand estimation regression and their fitted normal distribution curves for these two segments respectively.

distribution cannot be rejected at the 5% significance level.[7] We further similarly estimate the demand curves for the SKUs in the control group and test and verify the normality assumption with that group as well. Figure 2.4 demonstrates the Demand-Price scatter plots for two example industries, namely Electronic Products and Cosmetics, in panels (a) and (b) respectively. The overall logarithmic shape of the relationship is visible from these plots. The histograms for residuals for these two industries given in panels (c) and (d) visualize the normality of the distribution

[7]The only demand curve for which normality of the residuals could be rejected at 5% significance level is Home Improvement in 2013. The price-quantity scatter plot for this particular case shows a skewed, irregular shape. We believe the data draw for this case may be an anomaly. Since it also corresponds to only 0.8% of our data points, for simplicity, we expand our normality assumption to this case as well in our subsequent analysis.

of these error terms.

2.4.2.2 Structural Estimation of the Parameters

We next perform the structural estimation of our model's parameters based on our theoretical analysis. Before we proceed with it however, we need to discuss an element of our estimation and introduce notation for it: With the fast growth rate of the online retail business in China, consumer demand continues to be difficult to predict, and industry demand forecasts naturally include errors, which directly affect the retailers' order quantities. Therefore, in our estimation, we also incorporate potential forecast errors. We estimate forecast errors in a commonly employed manner (see, e.g., Terwiesch et al. [45]): For industry j let $\xi_j^{(y)}$ be the percentage industry forecast error in year y (2012 or 2013) on the log-mean of the demand. Then if for SKU i in industry j in year y, the actual demand is log-normal with log-mean $\mu_{ij}^{(y)}$ and log-standard-deviation is $\sigma_{ij}^{(y)}$, then the forecasted demand for this SKU is log-normal with mean $\mu_{ij}^{(y)}(1+\xi_j^{(y)})$ and standard deviation $\sigma_{ij}^{(y)}$. The industry-based forecast error approach reflects the reality as the forecasts in most products in an industry are highly correlated and in fact, in most cases analysts give forecasts based on industry rather than each individual SKU. It further eliminates overfitting that would tremendously undermine the estimation. For notation, for the rest of the paper, we will be denoting the c.d.f. of a log-normal random variable with parameters μ and σ by $F_{(\mu,\sigma)}$. Therefore, the c.d.f. of the forecasted demand for SKU i in industry j in year y will be denoted by $F_{(\mu_{ij}^{(y)}(1+\xi_j^{(y)}),\sigma_{ij}^{(y)})}$.

Let N be the number of industry segments, and for industry segment j, $M_j^{(12)}$ and $M_j^{(13)}$ be the number of SKU's whose suppliers obtained a commercial loan in 2012, and the number of SKUs that are financed by BIF in 2013, respectively. Given this notation and using the equilibrium quantity expressions (2.10) and (2.11), we can perform the following Nonlinear Least Squares (NLS) estimation:

$$\min_{\xi_j^{(12)},\xi_j^{(13)},c_g,\rho} \left\{ \sum_{j=1}^{N} \sum_{i=1}^{M_j^{(12)}} \left(Q_{ij}^{(12)} - F^{-1}_{(\mu_{ij}^{(12)}(1+\xi_j^{(12)}),\sigma_{ij}^{(12)})} \left(1 - \frac{c_{p(ij)}^{(12)}(1-a_l)\rho}{(1-a_l)((1-a_n)p_{ij}^{(12)} - a_n c_e) - a_l c_e + c_g} \right) \right)^2 \right.$$
$$\left. + \sum_{j=1}^{N} \sum_{i=1}^{M_j^{(13)}} \left(Q_{ij}^{(13)} - F^{-1}_{(\mu_{ij}^{(13)}(1+\xi_j^{(13)}),\sigma_{ij}^{(13)})} \left(1 - \frac{c_{p(ij)}^{(13)}(1+r_f)/(1-a_l)}{(1-a_l)((1-a_n)p_{ij}^{(13)} - a_n c_e) - a_l c_e + c_g} \right) \right)^2 \right\}. \quad (2.24)$$

Equation (2.24) minimizes the total squared discrepancy between the documented order quantity and the order quantity that is theoretically predicted by (2.13) and (2.18). The regression is performed to estimate the forecast errors in 2012 and 2013, $\{\xi_j^{(12)}, \xi_j^{(13)}\}$, and the parameters c_g and ρ, since these are the quantities not directly calculable or observable in the data or using public information sources, while all other parameters are as we describe below.

First, using information publicly available and obtained from direct interviews with JD's managers, we can calibrate c_e, r_{bi}, a_l, and a_n. From JD's financial disclosures unit returned product processing cost c_e is on average 8 Yuan per item.[8] According to the Supplier Finance Division of JD, annual interest rate for Buyer Intermediated Financing (r_{bi}) is 9% for all suppliers who are qualified for using the supplier financing service, which are the low-product-defect-rate suppliers as

[8]Presentation of JD CEO Qiangdong Liu at Zhong Guan Cun 100, Beijing, China, March 27 2014.

assessed by the company. The risk-free rate r_f, obtained from The People's Bank of China, is 6% for the period encompassed by the data.[9] Then, since by (2.17) we have $(1+r_f)/(1-a_l) = 1+r_{bi}$, plugging in $r_f = 0.06$ and $r_{bi} = 0.09$ and solving for a_l, we obtain $a_l = 0.0283$. That is, the data combined with our theoretical analysis estimates a 2.83% average defect rate for the high reliability suppliers. JD's total average consumer product return rate, including defective and non-defective products from high quality suppliers is approximately 4.2%.[10] Since a_n is the customer return rate of non-defective products, then the total return rate is $a_l + (1-a_l)a_n = 0.042$. Plugging in the estimated defect rate $a_l = 0.0283$, the estimate for a_n can then be calculated as 0.0141, i.e., 1.41%. Naturally, return rates vary across different products. Unfortunately, the exact return rate for each SKU is not available. Therefore, as it is very common in empirical studies, we take single rates a_l and a_n for all products as an approximation for the return rates taken as averages reflecting the best information available (see, e.g., Berry et al. [46], Cohen et al. [47], Allon et al. [48], among many others for similar empirical assumptions). This allows the analysis to avoid hundreds of distinct predictor variables in the regression, which would have drastically reduced the power of the estimation. Note that, in our analysis, we will similarly use a single c_g value to estimate as a representative average for the same reason and because it represents goodwill loss of JD in the eyes of the customers as a company, not for a specific industry or product.

In (2.24) we further need to calculate the unit production costs in 2012 and

[9] http://www.tradingeconomics.com/china/bank-lending-rate

[10] Interview with JD's CMO Yan Lan on November 15 2013.

2013, $\{c_{p(ij)}^{(12)}\}$ and $\{c_{p(ij)}^{(13)}\}$ respectively. We will first calculate the latter. From Proposition 3, by equation (2.19) for each SKU i in industry segment j, we have

$$c_{p(ij)}^{(13)} = \frac{w_{ij}^{(13)}(1-a_l)(Q_{ij}^{(13)} - \mathbb{E}[(Q_{ij}^{(13)} - D_{ij})^+])}{Q_{ij}^{(13)}(1+r_f)}, \tag{2.25}$$

where the expectation is computed using the corresponding demand distribution for each i, j estimated in Section 2.4.2.1. Equation (2.25) is an algebraic manipulation of the wholesale price equation, which results from the supplier being indifferent in equilibrium to participate or not. Having this in hand, we can estimate the unit production cost for each SKU in 2012, $c_{p(ij)}^{(12)}$ by adjusting the corresponding estimated production cost in 2013 $c_{p(ij)}^{(13)}$ for inflation. The inflation rate in China during 2012-2013 period is 2.6% (NBSC [49]), thus $c_{p(ij)}^{(12)} = c_{p(ij)}^{(13)}/1.026$.

Having all directly observable or calculable quantities in (2.24), we can now proceed with the estimation. However, there is one more unknown in the objective. Specifically, for 2012, we do not know for each supplier whether that supplier used a commercial loan or failed to secure a loan. Therefore, in order to find a consistent estimate we follow an iterative approach. We start with including all suppliers in the estimation in 2012, i.e., assuming all obtained commercial loans in 2012 and estimate (2.24).

Then we calculate the implied commercial loan interest rate $r_{cl(kj)}$ for each supplier as follows: Using the estimated parameters, for a given supplier k in industry j, define M_{kj} as the number of SKUs for that supplier. Further, define $R_{kj} = \sum_{i=1}^{M_{kj}} w_{ikj} D_{ikj}$, where the subscript $_{ikj}$ refers to product i of supplier k in industry segment j, and denote the c.d.f. and p.d.f. of R_{kj} by $F_{R(kj)}$ and $f_{R(kj)}$, respectively. For each supplier k in industry j, $F_{R(kj)}$ and $f_{R(kj)}$ can be calculated using the estimated demand distribution for each SKU i, $1 \leq i \leq M_{kj}$. Then, as in (2.16), by the bank's competitive interest setting, we have

$$\rho L_{kj}^{(12)} = \int_0^{L_{kj}^{(12)}\left(1+r_{cl(kj)}\right)} z f_{R(kj)}(z)dz + L_{kj}^{(12)}\left(1+r_{cl(kj)}\right)\left(1 - F_{R(kj)}\left(L_{kj}^{(12)}\left(1+r_{cl(kj)}\right)\right)\right), \tag{2.26}$$

where, since suppliers borrow only the required amount for production, $L_{kj}^{(12)}$ can be derived from (2.15) as

$$L_{kj}^{(12)} = \sum_{i=1}^{M_{kj}} c_{p(ikj)}^{(12)} Q_{ikj}^{(12)} - B_{0(kj)}^{(12)}. \tag{2.27}$$

Finally, in (2.27), again using the fact that the wholesale prices are set to make the suppliers indifferent to participate, $B_{0(kj)}^{(12)}$ can be calculated from (2.14) as

$$B_{0(kj)}^{(12)} = \sum_{i=1}^{M_{kj}} \frac{c_{p(ikj)}^{(12)} Q_{ikj}^{(12)} \rho - w_{ikj}^{(12)}(Q_{ikj}^{(12)} - \mathbb{E}[(Q_{ikj}^{(12)} - D)^+])}{\rho - \frac{1+r_f}{1-a_l}}. \tag{2.28}$$

Note that similar to Proposition 2, for given k, j, if there is a solution to (2.26), then it is unique. If there is no solution to this equation, however, this indicates that the corresponding supplier cannot have obtained a commercial loan according to our model, i.e., should not be included in the 2012 commercial loan estimation. We can take such suppliers out of the estimation for 2012 and iterate by reestimating (2.24) only with the suppliers, for whom the solution to (2.26) exists, and repeat until a

Table 2.2: Results for the NLS Regression for Parameter Estimation

	Estimate	t-value		
c_g	17.1921*** (1.1005)	15.6221		
ρ	1.1933*** (0.1150)	10.3765		
Industry Segment Forecasting Errors (ξ_j)	2012 Estimate	t-value	2013 Estimate	t-value
Auto parts	0.1733* (0.1015)	1.7073	0.2080*** (0.0191)	10.8900
Baby and Pregnancy products	0.0527*** (0.0228)	2.3050	0.1193** (0.0491)	2.4297
Ceramics	0.0133 (0.0113)	1.1770	0.0946*** (0.0138)	6.8551
Clothing	0.0535*** (0.0128)	4.1704	0.0949*** (0.0185)	5.1297
Coffee	0.0775*** (0.0184)	4.2119	0.1287*** (0.0171)	7.5263
Computer accessories	0.0735*** (0.0143)	5.1324	0.0995*** (0.0147)	6.7687
Cosmetics	0.0664*** (0.0241)	2.7552	0.0653*** (0.0250)	2.6120
Electronic products	0.0388*** (0.0046)	8.4348	0.0830*** (0.0102)	8.1373
Home improvement	0.0877*** (0.0062)	14.1452	0.1230*** (0.0092)	13.3696
Household appliances	0.1277** (0.0277)	4.6101	0.0840* (0.0515)	1.6311
Sporting goods	0.0617*** (0.0162)	3.8086	0.1112*** (0.0182)	6.1099
Staple goods	0.0483*** (0.0128)	3.7664	0.1264*** (0.0207)	6.1063
Wine	0.0153 (0.0425)	0.3609	0.1382*** (0.0111)	12.4505
Number of Observations: χ^2=100.021, p-value=0.0000	7098			

p<0.01 ***, p<0.05 **, p<0.1 *. Numbers in brackets are the corresponding standard errors for the parameters.

model-consistent estimation is obtained. We proceed by this method and obtain a model-consistent estimate, with 106 suppliers estimated to obtain commercial loans in 2012. The remaining eight suppliers are estimated not to have secured loans, producing only up to the amount their budgets allowed. The estimation results are given in Table 2.2. All our parameters in the estimation are identifiable as we discuss in detail in Section A.3 in the Online Supplement.

As can be seen in the table, the unit goodwill cost is estimated to be about

17.19 Yuan, or approximately \$2.83, which is similar in magnitude in other estimates of losses from stockouts in the literature (cf. Anderson et al. [50], Musalem et al. [51]). The estimate for ρ is 1.1933, which, by plugging in (2.26) can be used to estimate the interest rate for each supplier. Panel (a) of Figure 2.5 demonstrates the histogram for the estimated commercial loan interest rate for the 106 suppliers who, according to the regression outcome, obtained commercial loans in 2012. The estimated average commercial loan interest rate is 21.46%, which is on par with JD's own estimates. As the figure demonstrates, the rates for slightly more than half of the suppliers are concentrated around 20%. This is because for suppliers with high number of SKU's total revenue is high, and the risk of default from having insufficient revenue is low. As a result, such suppliers usually obtain standard rates available in the market, which are still significantly higher than the risk-free rate (6%), mainly based on the ex-ante defect risk of their products. For the remaining suppliers, the interest rates range from 20% to about 33%.

We can also see from the estimation that JD overforecasts the demand on average in each industry segment in both 2012 and 2013 with the possible exception of Ceramics and Wine in 2012 and Household appliances in 2013 (which are not significant at the 10% level). Our estimation indicates that JD over-forecasts the demand by an average of 6.84% in 2012, compared to 13.35% in 2013. The t-value of the difference between the two is -2.9011, which is statistically significant at the 5% level. A comparison of demand overforecasting in 2012 and 2013 by industry is given in panel (b) of Figure 2.5. The increase in overforecasting may have resulted from JD's lower than expected growth rate in 2013 and is consistent with the information

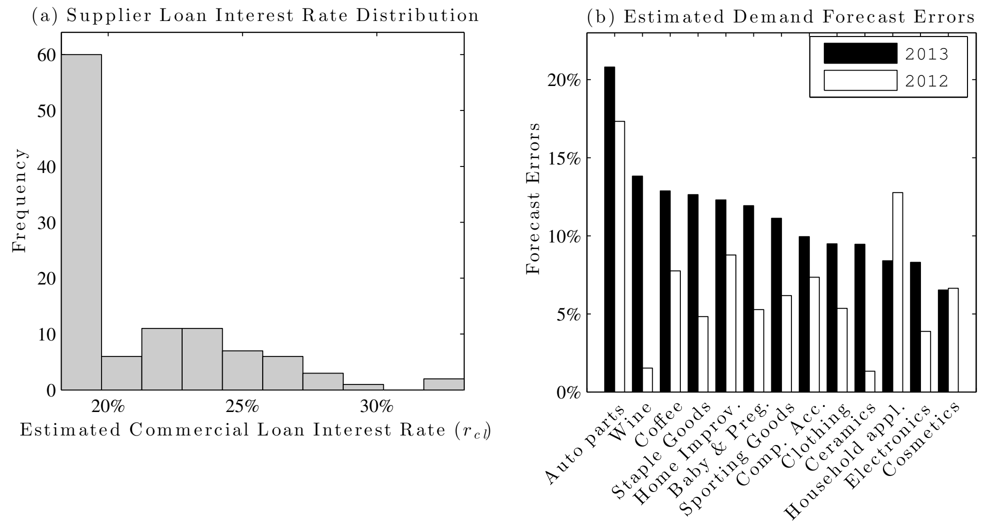

Figure 2.5: NLS Estimation Results. Panel (a) shows the estimated commercial loan interest rate distribution. Panel (b) shows the estimated industry segment forecast errors for 2012 and 2013.

we obtained from JD's managers about their demand estimates at the time. The demand overforecasting ranges from 1.33% (for Ceramics in 2012) to 20.80% (Auto Parts in 2013) but mostly varies around the 10% range.

2.4.3 Tests on Contract Characteristics and Borrowing

In this section, based on the results from our theoretical analysis from Section 3.3 and our estimation from Section 2.4.2, we present and test hypotheses on the contract performance. In particular, we test the effect of BIF on financing costs, wholesale prices, and the order quantities as well as how supplier borrowing behavior changes under BIF.

We start with testing the financing costs. As we have shown in part (i) of Proposition 4, the interest rate on the loan should be higher compared to the case where the supplier uses BIF. So our first hypothesis is as follows:

Hypothesis 1 *Suppliers' loan interest rates are higher under commercial loans compared to BIF.*

In order to test Hypothesis 1, we utilize a one sample t-test to compare the estimated interest rates on the commercial loans used by 106 suppliers in 2012 to the interest rate set by JD for BIF. From our structural estimation of our model in Section 2.4.2.2, the average interest rate for commercial loans r_{cl}, is found to be 21.46%. The BIF interest rate, $r_{bi} = \frac{1+r_f}{1-a_l} - 1$, is known to be flat at 9%. The t-test for the sample shows that commercial loan interest rates are lower with a t-value of 41.28, which is significant at 0.01% level. Hence, we can conclude that Hypothesis 1 is supported, i.e., financing costs are lower under BIF than commercial loans.

We next test the effect of BIF on wholesale prices. As we have shown in part (ii) of Proposition 4, when the consumer demand variation is sufficiently low, BIF wholesale price is lower than the commercial loan wholesale price. As Figure 2.3(b) shows, this is true for small log-standard-deviation-to-log-mean ratios already in the order of 0.01. From our demand estimation in Section 2.4.2.1, we can calculate that the average σ_{ij}/μ_{ij} ratio for our SKUs is 0.0088. Therefore, we expect that the wholesale prices under BIF to be lower compared to those under commercial loans. We would like to test this conclusion directly as well as controlling for the retail price. Thus, we have the following hypotheses to test:

Hypothesis 2

(a) Wholesale prices are lower under BIF compared to commercial loans.

(b) Wholesale-to-retail price ratios are lower under BIF compared to commercial

	w			w/p		
	BIF	CG1	CG2	BIF	CG1	CG2
Change from 2012 to 2013	-3.20%	-1.74%	-1.28%	1.40%	3.63%	3.78%
Two sample t-test vs. BIF		**-4.322***** **(0.0001)**	**-3.037**** **(0.021)**		**-2.496***** **(0.006)**	**-1.803**** **(0.036)**
Two sample t-test CG1 vs. CG2			-1.165 (0.483)			-0.027 (0.642)

	$Q/E[D]$		
	BIF	CG1	CG2
Change from 2012 to 2013	-12.17%	-26.69%	-19.48%
Two sample t-test vs. BIF		**2.786***** **(0.002)**	**1.902**** **(0.029)**
Two sample t-test CG1 vs. CG2			-1.507* (0.066)

Table 2.3: The percentage changes for 2013 over 2012 for wholesale price (w), wholesale-to-retail price ratios (w/p), and normalized order quantities ($Q/E[D]$) for the BIF and the Control Groups 1 and 2 (CG1 and CG2), and the corresponding pairwise two-sample t-test results. For the two-sample t-tests, the first number for each pair is the t-value, and the number in brackets is the corresponding p-value. The markers indicate: p<0.01: ***, p<0.05: **, and p<0.1: *.

loans.

We will test both parts of this hypothesis through a commonly employed difference-in-differences approach (see, e.g., Ashenfelter and Card [52], LaLonde [53], Card [54], Meyer et al. [55], among many others). For this, we will use the two control groups in our dataset, Control Group 1 who voluntarily chose not to use BIF in 2013, and Control Group 2, who were excluded from BIF by JD. We will first calculate the benchmark percentage changes in (a) wholesale prices, and (b) wholesale-to-retail price ratios between 2012 and 2013 for the two control groups. Then we will calculate the corresponding changes for the 106 suppliers that participated in BIF and for whom our estimation in Section 2.4.2.2 indicates had commercial loans in 2012. If the change in the wholesale price for the BIF group is lower than that of the control groups, this indicates that under BIF, suppliers had an extra wholesale price reduction effect over and beyond one would obtain under the same financing structure from 2012 to 2013. Table 2.3 summarizes the percentage changes in wholesale prices for each group.

As can be seen from the table, the average wholesale price drop between 2012 to 2013 for the Control Groups 1 and 2 are 1.74% and 1.28%, respectively. In comparison, it is 3.20% for the BIF group. As indicated by Table (2.3), two-sample t-test results indicate that there is no significant difference between the price drops of the two control groups. However, the difference in price drop between the BIF group and both control groups are significant. Therefore, the data supports that the wholesale prices are lower with BIF compared to commercial loans over and beyond the base expected level between 2012 and 2013, and hence Hypothesis 2(a) is supported.

For Hypothesis 2(b), to take into account the effect of the change of overall retail price in the market, we calculate the wholesale-to-retail price ratio w_{ikj}/p_{ikj} for each SKU, in 2012 and 2013, for both the control and BIF groups and calculate the change in this ratio from 2012 to 2013. Again as can be seen from Table 2.3, for the two control groups, the wholesale-to-retail price ratio increases between 2012 to 2013 are 3.63% and 3.78%, respectively, and the difference between the two is not statistically significant. In contrast, the increase in the wholesale-to-retail price ratio for the BIF group is 1.40%, which significantly differs from those of both control groups. Hence, Hypothesis 2(b) is also supported.

Next, we look at the effect of BIF on order quantities. From our estimation in Section 2.4.2.2, we have $\rho = (1+r_f)/(1-\eta_a) = 1.1933$. Plugging in $r_f = 6\%$ and solving for η_a, we obtain $\eta_a = 0.1117$. According to our model, as we have shown in part (iii) of Proposition 4, for suppliers that are financed through BIF, order quantities increase if $\eta_a > 1-(1-a_l)^2$. Since we estimated a_l as 0.0283 in Section 2.4.2.2, we then have $\eta_a = 0.1117 > 1-(1-a_l)^2 = 0.0558$, i.e., our theory predicts that the BIF will have an effect of increasing the order quantities. Hence we have the following hypothesis:

Hypothesis 3 *Order quantities increase under BIF compared to commercial loans.*

We again perform this test with a difference-in-differences approach. In particular, for each SKU i in industry j in the control group, we normalize the order quantity by the mean forecasted demand for that SKU for 2013 to control for the demand and forecast effects on quantity. That is, we calculate $Q_{ij}^{(13)}/(E_{(\mu_{ij}^{(13)}(1+\xi_j^{(13)}),\sigma_{ij}^{(13)})}[D_{ij}])$, where, by log-normality of the demand distributions, for each (i,j) we have

$$E_{(\mu_{ij}^{(13)}(1+\xi_j^{(13)}),\sigma_{ij}^{(13)})}[D_{ij}] = e^{\mu_{ij}^{(13)}(1+\xi_j^{(13)})+(\sigma_{ij}^{(13)})^2/2}\,. \tag{2.29}$$

Repeating the same for 2012, we can then calculate the percentage change from 2012 to 2013, which is again given in Table 2.3.

As can be seen in the table, the average decrease for normalized order quantities for Control Groups 1 and 2 are 26.69% and 19.48% respectively, and these two values are not significantly different at the 5% level. For the BIF group, the average decrease is 12.17%, and is significantly different compared to both benchmark control groups at the 5% level. Therefore Hypothesis 3 is supported. Note that a pairwise comparison of the normalized quantities between the BIF and each one of the control groups controls for not only the forecasted means and the year-to-year effects, but also for the cross-supplier and cross-SKU effects since the percentage changes are calculated for each SKU internally and separately.

Finally, we would also like to test how the supplier borrowing behavior is affected under BIF. In particular, by Propositions 2 and 3, a supplier borrows $c_pQ^*_{cl} - B_0$ and $c_pQ^*_{bi} - B_0$ under the commercial loan and BIF respectively. As we have shown in part (iii) of Proposition 4, our theory predicts that supplier borrowing as a percentage of production costs increases under BIF. Therefore, we have the following hypothesis:

Hypothesis 4 *Suppliers borrow a higher percentage of their production costs under BIF than under commercial loan.*

In order to analyze and test Hypothesis 4, we first need to calculate the loan-to-cost ratios, $L/c_pQ^* = (c_pQ^* - B_0)/c_pQ^*$, for 2012 and 2013. As we had discussed in Section 2.4.2.2, estimates for unit production costs in 2013 can be calculated as given in (2.25), and the estimates for 2012 can be calculated by adjusting the SKU unit cost estimates by inflation. We do already have the loan data for 2013, so we can calculate the loan-to-cost ratio for 2013 directly. In order to calculate the loan-to-cost ratio for 2012, we need to use the estimate for the commercial loan borrowed by each supplier k in industry j who is estimated to get a loan in 2012, as we again had calculated in Section 2.4.2.2, given by equations (2.27) and (2.28). After calculating the ratio for each supplier in 2012 and 2013, we find that the average loan-to-cost ratio is 31.97% in 2012 and 41.71% in 2013. The t-value for testing the difference between the two samples is -2.0569 with a p-value of 0.0215. In order to check for robustness, we also perform the non-parametric Wilcoxon rank-sum test on the loan-to-cost ratios, which gives a sum of the signed ranks value of 1537, with a p-value of $1.245 \cdot 10^{-8}$. Therefore, we can conclude that the supplier borrowing as a percentage of the costs is higher under BIF compared to commercial loans, and Hypothesis 4 is supported.

There is one more thing we have to pay attention to in this test. If the budget levels in 2013 are significantly lower than the budget levels in 2012, then the loan percentages in 2013 could be higher than those in 2012, simply because the suppliers have lower starting cash positions. Therefore, in order to check the differences between the supplier budget levels, by (2.20), we calculate the 2013 budget for supplier k in industry j as

$$B_{0(kj)}^{(13)} = \sum_{i=1}^{M_{kj}} c_{p(ikj)}^{(13)} Q_{ikj}^{(13)} - L_{kj}^{(13)} \left(\frac{1 - a_l}{1 + r_f} \right). \tag{2.30}$$

Estimated supplier budget levels for 2012 were calculated by (2.28). Performing the calculations, the estimated 2012 average supplier budget level is 3.04 Million Yuan, while it is 3.85 Million Yuan in 2013. The t-value for the differences in the two samples is -2.0325, with a p-value of 0.0211. Wilcoxon rank-sum test yields a score of 13835.58, with a p-value of $2.2 \cdot 10^{-16}$. Hence we can conclude that the budget levels were higher in 2013 compared to 2012. That is, the suppliers' borrowing is higher under BIF as a percentage of their production costs, despite their having higher starting budgets on average.

2.4.4 Empirical Efficiency Analysis

In this section, we present efficiency analysis based on the results from both our theoretical analysis and the data. By combining our theoretical results in Section 3.3 with our demand and structural estimations in Section 2.4.2, we will make a calibrated counterfactual analysis of the outcome and supply chain surplus under commercial loan financing under the conditions of 2013 and compare to the actual BIF outcome. Specifically, with estimates for B_0, c_p, c_g, $\{\xi_j\}$, a_l, a_n, r_{cl} and SKU demand distributions in hand, we can calculate the estimated wholesale price, order quantity and the expected supply chain profit for each SKU using Proposition 2 under commercial loan financing. Similarly, we can also calculate the optimal order quantity and the expected profit for the first-best solution, as well as the expected supply chain profit under Buyer Intermediated Financing. We can then measure the efficiency of each scheme and the efficiency gains obtained by employing BIF using the first-best outcome as a benchmark, as well as the dollar savings for varying η_a values with and without forecast errors.

Table 2.4 presents these results. In particular, it exhibits the ratio of the mean of the optimal order quantity in each scheme as a fraction of the order quantity from the first best solution, the mean of optimal wholesale price under each scheme, and the ratio of expected profit for each scheme over the first-best total profit for varying η_a levels. As we had shown in Section 2.4.3, the implied η_a from our structured

Table 2.4: Empirical Efficiency Analysis

	Without Forecasting Errors					
	Commercial Loan				BIF	Estimated Change
	(η_a=0.08)	**(η_a=0.1117)**	(η_a=0.14)	(η_a=0.17)		
Order Quantity	0.9062	**0.8766**	0.8518	0.8240	**0.9782**	**11.27%**
Wholesale Price	171.3892	**172.1908**	173.0026	173.7814	**167.3740**	**-2.80%**
Total Profit	0.8902	**0.8601**	0.8381	0.8136	**0.9536**	**10.87%**
	With Forecasting Errors (Using estimated ξ_j^{13})					
	Commercial Loan				BIF	Estimated Change
	(η_a=0.08)	**(η_a=0.1117)**	(η_a=0.14)	(η_a=0.17)		
Order Quantity	0.9385	**0.9034**	0.8751	0.8428	**1.0250**	**13.46%**
Wholesale Price	181.4961	**182.6399**	183.9228	185.3919	**180.3089**	**-1.28%**
Total Profit	0.7371	**0.7068**	0.6814	0.6575	**0.8359**	**18.27%**

estimation is 0.1117. We construct the panel for the Commercial Loan scenarios by varying η_a around this value by an approximately equal interval size of 0.03. As can be seen from the table, due to the forecast error, the retailer on average orders more than the first best order quantity under BIF. The quantity increase by employing BIF over commercial loan increases as η_a increases, ranging from 7.94% to 18.71% without forecast errors, and 9.21% to 21.62% with forecast error as η_a moves from 0.08 to 0.17. At the model estimated η_a level, the improvement in order quantity is 11.27% without forecast errors and 13.46% with forecast errors. Estimated wholesale price drop with BIF also increases with η_a reflecting the increased relative advantage of BIF of commercial loans in financing costs. At the estimated η_a level of 0.1117, the expected wholesale price drop is 2.80% without forecast errors, and 1.28% with forecast errors.

Increased quantities and decreased wholesale prices get reflected on increased profit gains as η_a increases. As η_a moves from 0.08 to 0.17, profit gains with BIF range from 7.12% to 17.21% without forecast errors, and 13.41% to 27.13% with forecast errors. At the model estimated η_a level, the expected profit gains are 10.87% and 18.27% with and without forecast errors, respectively. From the sales data set, the average gross margin for JD can be calculated as approximately 15.68% and the total revenue for the 106 companies that used BIF can be calculated as approximately \$300M. Using our estimate of 18.27% expected increase in profits, we can then conclude that employing BIF resulted in approximately \$8.6M savings for JD for the companies in our sample data set. Note that our data covers only about 1 Billion Yuan total financed through BIF by JD whereas the total amount financed by the company in 2013 was approximately 8 Billion Yuan. Therefore, the company's projected total savings from BIF in 2013 reaches upwards of \$68M for 2013.

2.5 Concluding Remarks

In this paper we studied a novel financing scheme that is recently employed by some large retailers to provide accessible financing to small suppliers who are facing budget constraints. We game-theoretically compared the outcome of the new buyer intermediated financing scheme to that of a traditional commercial loan. We further estimated the model parameters using retailer data and empirically demonstrated the improvements in the contract characteristics and channel efficiency gains introduced.

In our model, we used a single shot setting to model the buyer's ordering process. Since the data we used in our empirical study is annual for order quantity and demand, and since in a one year cycle, the buyer orders more than once, there may be some temporal aggregation bias in our results. However, we believe this does not affect the gist of the main findings and conclusions from our paper. This is because, even though the buyer orders more than once throughout the year, the usual industry practice, including that of JD confirmed by our interviews is that the order quantity decisions are done much less frequently. For most products, the order quantity decisions are mostly set once a year, and replenishment is done on a schedule, while for other products the cycle is six months. Further, deviations from the replenishment schedule are seldom. Therefore, the quantity decisions, which is what we are estimating in our analysis, approximately fit the one shot setting we have with a one year period length. Hence, even though there is some temporal aggregation bias present in our structural estimation, we do not expect our main conclusions to be affected strongly by it. A future avenue for research could be analyzing more granular order data to confirm and extend our findings in this paper.

One possible question here is why retailers do not simply communicate the supplier's type to the bank informally based on their long term relationships with them. Setting the transactions based on such communications is unfortunately not possible in many cases including JD's. First, regulations and restrictions in lending create obstacles for such non-enforceable contracts to emerge - especially in emerging markets. For instance, in JD's case, in China, lending of banks have strict controls and follow rigid rules (both internal and government enforced) that prevent them from entering into such informal contracts with no financial guarantee, formal underwriting, or monetary back up. In fact, in JD's case this causes a second related issue that makes the implementation of such relationship based contracts unlikely: because of bank rules and government regulations, big banks in China are usually unable to finance small, risky suppliers. As a result without the retailer's involvement as in BIF, the suppliers are usually financed by high interest commercial lenders called "micro-loan" companies at rates higher than 20%. Large retailers do not usually have long term relationships with such companies. In contrast, by backing the suppliers' loans under BIF, JD is able to bring the interest rate to sufficiently low levels that big government-backed Chinese banks are capable of providing the financing within their internal and external regulatory restrictions. It should also be noted that although incomplete contracts based on long-term relationships are common among supply chain partners (see, e.g., Tunca and Zenios [56]), they are not very common among financial institutions, which often require more formal collateral and underwriting for their transactions. In fact, JD (and other large retailers who employ similar financing schemes) would have much preferred facilitating financing through informal information exchanges if they could, which would have allowed them to avoid taking the extra risk of underwriting the suppliers' loans.

Another avenue of future research could be studying long term quality investments by the suppliers. Considering the positive effects that BIF financing could have in the long run, suppliers who are not currently considered low risk may invest in improving the quality and reliability of their product so that they can get BIF financing. Such a strategy would bear fruits in a longer time horizon than that in our current model and is beyond the scope of the current paper. However, a future study that extends the model to quality improvement investments by the suppliers and perhaps tests it on long-term data can shed light onto the role of buyer financing in long term industry dynamics of quality improvement.

Our study provides theory and evidence on the efficiency of the Buyer Intermediated Supplier Financing schemes that are gaining increased usage in supply chains, especially in emerging economies. This innovative approach in easing suppliers' budget constraints can help not only improving supply chain efficiency significantly, but also help many small suppliers to gain their footing in the industry and grow their business, ultimately helping the development of economies, trade growth and value generation around the globe. The insights obtained from our study and future follow up studies can contribute to the understanding of these useful financing schemes and to their evolution and progress in practice.

Chapter 3: The Effectiveness of Supplier Buy Back Finance: Evidence from Chinese Automobile Industry

3.1 Introduction

Lack of access to cheap finance appears to present a perpetual difficulty for small buyers. The problem is caused by a constellation of factors ranging from lack of credit history to lack of effective financing scheme tailored to small companies. As a result, small buyers have very limited, if any, source of finance, which often comes with very high interest rate. Realizing that the budget constrained buyer could hamper the supply chain efficiency, suppliers who are large in size and financially sound start to launch in-kind finance or intermediate between bank and small buyers.

Trade credit contract, which is the most frequently used in-kind finance for funding buyers, incurs a high implicit cost (Cunat [4]) and could leave buyer in an adverse condition when facing bleak downstream demand. Thus, to better support buyer in case of both high and low demand realization, companies in China (Jianxin and Jiayin [57]) start to adopt a novel financing scheme in which supplier intermediates between buyer and bank by guaranteeing to buy back the unsold products on loan.

Buy back contract serves two roles in the presence of financially constrained buyers. The first role is identical to the role that a buy back contract is traditionally designed for: to transfer the downstream demand risk from the buyer to the supplier and encourage the buyer to stock more aggressively. The second role, however, is less studied in the previous literature. The buy back agreement could also free the bank from the risk of buyer default, since financial restitution from the supplier assures the buyer sufficient budget to pay back the loan. In other words, buy back contract could not only induce higher order quantity, but also help the buyer secure finance. With all the benefits brought to the supply chain, however, buy back agreement could also be detriment to the channel efficiency. In the context where the products to be bought back are fragile, or large and heavy (trucks), it would be costly for the upstream party to carry out its buy back policy. For example, it may not be optimal to buy back a large amount of products when the products to be returned are shipped from remote place and the local labor is expensive. As a result, the overall impact of the buy back contract on the supply chain performance is unclear and needs to be investigated.

One example of a large supplier who employs buy back financing to its buyers is Foton Motor, a leading automotive company in China that mainly manufactures light and heavy-duty trucks. Foton achieved an annual revenue of 5 Billion dollars in 2014 and most of their vehicles are sold to the customers through buyers (dealers) that are small, remotely located and in need of finance to better meet the local demand. Foton Motor therefore launched its own financing scheme to the qualified buyer since 2010, and nowadays approximately 40% of Foton Motor's buyers are using Foton Motor's financing on a regular basis. Foton Motor's buy back financing scheme works as follows: Foton Motor guarantees its buyer and bank that Foton will buy back all unsold products that are on loan by the maturity of the loan. The buyer then makes its order decision, with part of its purchase supported by bank's loan and rest by the buyer's own budget. When the loan matures, if the revenue obtained by the buyer is enough to cover the loan, the buyer will repay the loan, otherwise Foton will step in and buy back the unsold products that are on loan and so that buyer can better fulfill the loan.

The properness of risk reallocation underpins the success of buy back finance, it is therefore critical to recognize if it's worthwhile for supplier to shoulder extra risk to buy back the unsold products. If so, what is the optimal buy back contract for supplier to employ? In addition, the incentive problem arose from the contract design is of our particular interests. Should the supplier urge its buyer to sell the products on loan first (denoted as Last In First Out, or LIFO for abbreviation, buy back scheme since the products purchased on loan are sold first), or should the supplier encourage the buyer to give priority to sell the products purchased by the buyer's budget(denoted as FIFO scheme as the products purchased using buyer's own budget are sold first)? Moreover, buying back vehicles tend to be more costly than buying back products of small volume such as clothing or books. How costly it is to buy back a truck from a certain area, and how will the buy back cost in turn affect the operational decision making are also of our interests. Last but not least, how is the efficiency of the currently implemented buy back contract, which is LIFO buy back scheme, compare to FIFO buy back financing, full buy back financing where supplier agrees to buy back any unsold products, or other traditional financing schemes? These are the questions we intend to answer in this paper.

A two-echelon supply chain with a potentially budget-constrained buyer is constructed to capture the interplay between each party. We start by presenting the base case where the retailer has no access to external capital and cannot return unsold products. The base case reflects the difficult situation faced by most small buyers. Together with the base case we also establish the commercial loan scenario as one of the benchmarks. We then model the buy back financing based on the financing practice used by Foton Motor (LIFO buy back scheme) and develop to variants of the commonly used buy back financing methods, namely, FIFO and Full buy back financing schemes. We then compare the efficiency of all the financing alternatives mentioned above. The results from our theory are tested using data obtain from Foton Motor. We perform structural estimation to derive parameters that are not provided in the data, which are further utilized to conduct the counterfactual analysis.

The rest of the paper is structured as follows. Section 3.2 reviews the previous literature. Section 3.3 lays out the model framework, describes the financing schemes we study, and provides the theoretical analysis and the comparison of the financing schemes. Section 3.4 presents our empirical analysis, including model parameter estimation, hypothesis development and tests, and efficiency analysis. Section 3.5 offers our concluding remarks. All proofs are given in the appendix.

3.2 Literature Review

There is an extensive literature in OM field that examines how to finance a budget-constrained retailer from a theoretical point of view. Tunca and Zhu [58] include a comprehensive literature review on research about trade credit. Moreover, Dada and Hu [9] show that in a Stackelberg game setting, a capital constrained newsvendor would borrow from bank and order an amount that is less than what would be optimal if the cost of borrowing is not too high. Luo and Shang [17] consider a firm that both offers and receives trade credit to other parties in the supply chain and periodically orders inventory to satisfy demand in a finite horizon. They prove a optimal myopic policy when the sales collection period is no shorter than the purchase payment period. Also, they suggest that supplier's liquidity provisions can remedy the distortion of demand information. Zhou and Groenevelt [10] investigate the case when the supplier provide subsidies to a budget constrained retailer. Caldentey and Chen [11], Kouvelis and Zhao [12] (Kouvelis and Zhao [13], Kouvelis and Zhao [12]) and Jing et al. [14] examine the interplay between a supplier, a budget constrained retailer and bank, demonstrating that when bank loans are competitively priced, retailers will prefer supplier financing to bank financing if an optimally structured trade credit contract is offered - but when the bank has market power in setting the interest rate, either form of financing can be preferable depending on the market parameters. Yang and Birge [15] extend previous works by showing that even when bank financing and supplier financing can be used jointly, supplier financing is still preferred to bank financing. In addition, with the aid of a sample of firm-level data, they find that the financing pattern predicted by their model is used by a wide range of firms.

In juxtaposition to the theoretical analysis on trade credit financing, there is a large body of research in Finance field studying trade credit contract from an empirical angel. Klapper et al. [6] show that the largest and the most creditworthy buyers tend to enjoy the longest maturities from smaller suppliers, and that riskier buyers tend to receive discount for early payment. Giannetti et al. [5] demonstrate that the nature of the transacted good affects the use of trade credit in the sense that suppliers who offer differentiated products have larger accounts receivable than those who offers standardized goods. They also show that firms receiving trade credit are more likely to obtain financing from relatively uniformed bank. Cunat [4] points out that the high implicit interest rates of trade credit are resulted from insurance and default premiums that are amplified by the relatively high cost of funds obtained by the suppliers.

Our research is also closely related to literature on buy back contract. Pasternack [59] first studies a buy back contract that could induce channel coordination. Emmons and Gilbert [60] show that both the manufacturer and the retailer could benefit from back back policy under a price dependent setting. Bernstein and Federgruen [61] examine a price-discount contract that includes a wholesale price and a buy-back rate. They show that coordination is obtained when both of the contract terms depend on the chosen retail price. Cachon and Lariviere [62] conclude that revenue sharing contract is equivalent to buy back contract in the newsvendor case in the sense that for any buyback contract, there exists a revenue sharing contract

Table 3.1: Model Notation

w:	Unit wholesale price for the product
Q:	Retailer's order quantity
D:	Consumer demand
F, f:	c.d.f. and p.d.f. for D
p:	Unit retail price for the product
c_p:	Supplier's unit production cost
c_b:	Supplier's unit buy back cost
r_f:	Risk-free interest rate for each period
B_0:	Supplier's initial cash position at t=0.
B_1:	Supplier's cash position before paying the bank loan at t=1
L:	The loan amount
Π_r:	Retailer's expected net profit at time t=1
Π_s:	Supplier's expected net profit at time t=1

that achieves the same cash flows. In addition, revenue sharing contract is equivalent to price discounts in the price-setting newsvendor case. Gan et al. [63] demonstrate that supply chain with a risk-neutral supplier and a downside-risk-averse retailer cannot be coordinated by buy back contract. Song et al. [64] indicate that at optimality, the efficiency of the decentralized channel for distribution-free buyback contracts only hinges on the curvature of the deterministic demand part. Our paper differs from the existing literature by examining the role of buy back contract in the context where buyer is budget constrained. We also studies if suppliers will exercise price discrimination to between those who use back back contract and those who don't.

3.3 Modeling Framework

In this section, we present our game theoretical framework of the financing structures in the aim to lend a theoretical framework to our structural estimation.

We start with the general model description and then provide the details of the base case as well as four benchmark financing models, namely the Commercial Loans, LIFO buy back, FIFO buy back and Full Buy back.

Consider a two-layer supply chain with a large upstream supplier and a downstream retailer whose initial capital can be insufficient to order what is optimal given the projected demand. The retailer can be financed by a third-party bank. At the same time, the supplier is large enough in the sense that he can always cover his production and repay a loan he has committed to pay.

We start by specifying the timeline. There are two time periods in the model, indexed as $t = 0, 1$. At time $t = 0$, the supplier offers the retailer a wholesale price w. The retailer, foreseeing the upcoming demand, responds with the order quantity Q. If the retailer's cash position at $t = 0$ is insufficient to pay the supplier, she will resort to an outside bank for liquidity. Also at $t = 0$, after the payment is made in full, supplier delivers the products to the retailer. At $t = 1$, demand D, which follows a c.d.f. $F(\cdot)$ and a pdf $f(\cdot)$, realizes.

3.3.1 Financing Alternatives

3.3.1.1 Base Case

We start with the base case scenario where retailer has no access to external finance and needs to make ordering decision without any buy back commitment from the supplier. The base case reflects the condition faced by most small retailers in reality. Denote the base case by subscript $_{bc}$. In this circumstance, the retailer's problem is:

$$\max_{Q\geq 0}\Pi_r(Q,w) = \max_{Q\geq 0}\mathbb{E}[p\min\{Q,D\} - wQ(1+r_f)\}].$$
$$\text{s.t.}\quad B_0 - wQ \geq 0.\ \textbf{(Retailer's production budget constraint)} \tag{3.1}$$

The supplier's problem is

$$\begin{aligned}\max_{w\geq 0}\Pi_s(Q,w) = & \max_{w\geq 0}\mathbb{E}\big[(w-c_p)Q(1+r_f)\big] \\ \text{s.t.}\quad & \Pi_r(Q,w) \geq B_0(1+r_f),\ \textbf{(IR)}\end{aligned} \tag{3.2}$$

3.3.1.2 Commercial Loan

We then consider commercial loan scenario in which bank directly lends to the retailer. We denote the commercial loan case by the subscript $_{cl}$. The time line follows the general outline: At $t = 0$, the supplier first offers a wholesale price w, retailer then decides the order quantity Q. To pay the supplier in full, the retailer may need to borrow a loan L, with payable due at $t = 1$, from the bank. After receiving the payment, the supplier produces and delivers the goods. At $t = 1$, the consumer demand and the retailer revenues materialize. The retailer will then pay the loan back to the bank to the extent possible. In the meantime, the bank sets its interest rate competitively. Denote the risk-free rate by r_f and the bank's interest rate by r_{cl}. Also denote the retailer's and the supplier's expected profits as Π_r and Π_s, respectively.

The retailer has to make sure that she borrows enough to cover the payment for the order. The supplier, on the other hand, has to ensure that the retailer's terminal cash position will be no less than what he would otherwise obtain by investing his money on the risk free asset.

The retailer's problem for determining the order quantity and the amount to borrow from the bank can then be written as

$$\begin{aligned}
\max_{Q,l\geq 0}\Pi_r(Q,w,l) = \quad & \max_{Q,l\geq 0}\mathbb{E}[p\min\{Q,D\} - \min\{l(1+r_{cl}),B_1\} + (B_0 + l - c_pQ)(1+r_f)] \\
\text{s.t.} \quad & B_0 + l - wQ \geq 0, \ \textbf{(Retailer's production budget constraint)} \\
& l(1+r_f) = \textstyle\int_0^\infty \min\{l(1+r_{cl}),B_1\}f(D)dD\,. \\
& \qquad\qquad \textbf{(Bank's competitive interest setting equation)}
\end{aligned} \tag{3.3}$$

Hence the supplier's problem when the retailer financing is obtained through a commercial loan can be written as

$$\begin{aligned}
\max_{w\geq 0}\Pi_s(Q,w) = \quad & \max_{Q,w\geq 0}\{\mathbb{E}[(w-c_p)Q(1+r_f)]\} \\
\text{s.t.} \quad & \Pi_r(Q,w,L) \geq B_0(1+r_f), \ \textbf{(IR)} \\
& \text{where } L \text{ solves the retailer's optimization problem} \\
& \text{as given in (3.3). } \textbf{(IC)}
\end{aligned} \tag{3.4}$$

3.3.1.3 Buy-Back Finance

Buy-back finance is the core model we study in this paper. We consider three buy-back arrangements, namely Last-n First-Out (LIFO), First-In-First-Out (FIFO) and Full buy back (FBB). For LIFO, for the contract purposes, it is considered that the retailer sells the products that are purchased using the loan first, and she starts to sell the products that are purchased using her own budget only when the products on loan are sold out. For FIFO, things proceed the opposite way: products purchased using retailer's own budget are considered to be sold first. We denote LIFO with the subscript $_{lf}$, and the FIFO financing with the subscript $_{ff}$. In both cases, the supplier promises to buy back the unsold products that are purchased on loan.

The timeline for buy back finance proceeds as follows: at $t = 0$, supplier offers a wholesale price w for the product, and the retailer sets her order quantity Q accordingly. If retailer does not have sufficient budget to pay for the purchase, she obtains a loan L from the bank with interest rate r_{lf} for the LIFO case and r_{ff} for the FIFO scenario. The bank sets the interest rate competitively in each case. The supplier then delivers the products, and the retailer pays in supplier in full. Any cash left by the retailer will be invested on the risk free asset. At $t = 1$, consumer demand is realized. Supplier buys back all the unsold products that are on loan. Retailer then pays back the loan to the extent possible.

We start by examining the retailer's objective function in the LIFO case:

$$\begin{aligned}
\max_{Q,l\geq 0}\Pi_r(Q,w,l) = \quad & \max_{Q,l\geq 0}\Big\{\mathbb{E}\big[p\min\{Q,D\} + w\big(\tfrac{wQ-B}{w} - D\big)^+ \\
& \qquad - \min\{l(1+r_{lf}), B_1\} + (B_0 + l - wQ)(1+r_f)\big]\Big\} \\
\text{s.t.} \quad & B_0 + l - wQ \geq 0, \; \textbf{(Retailer's production budget constraint)} \\
& l(1+r_f) = \textstyle\int_0^\infty \min\{l(1+r_{lf}), B_1\} f(D)dD\,. \\
& \qquad \textbf{(Bank's competitive interest setting equation)}
\end{aligned} \tag{3.5}$$

The first two terms in retailer's objective function is B_1, her budget level after supplier buys back the unsold products that are on loan. The third term is her loan repayment, and the final term is the $t = 1$ value of her left over budget invested in the risk-free asset at the end of $t = 0$.

The supplier's problem when the retailer financing is obtained through a LIFO buy-back contract can be written as

$$\begin{aligned}
\max_{w\geq 0}\Pi_s(Q,w) = \quad & \max_{w\geq 0}\mathbb{E}\big[(w-c_p)Q(1+r_f) - (w+c_b)\big(\tfrac{wQ-B}{w} - D\big)^+\big] \\
\text{s.t.} \quad & \Pi_r(Q,w,L) \geq B_0(1+r_f), \; \textbf{(IR)} \\
& \text{where } L \text{ solves the retailer's optimization problem} \\
& \text{as given in (3.5). } \textbf{(IC)}
\end{aligned} \tag{3.6}$$

We now examine the FIFO buy-back financing scheme. FIFO differs from LIFO only in the buy back term: For FIFO, products purchased using retailer's budget are sold first. As a result, the retailer's objective function in the FIFO scheme is

$$\max_{Q,l\geq 0}\Pi_r(Q,w,l) = \max_{Q,l\geq 0}\Big\{\mathbb{E}\big[p\min\{Q,D\} + w\big(\tfrac{wQ-B}{w} - \big(D-\tfrac{B}{w}\big)^+\big)^+ \\ - \min\{l(1+r_{ff}),B_1\} + (B_0+l-wQ)(1+r_f)\big]\Big\}$$

$$\text{s.t.}\quad B_0+l-wQ \geq 0,\ \textbf{(Retailer's production budget constraint)}$$

$$l(1+r_f) = \textstyle\int_0^\infty \min\{l(1+r_{ff}),B_1\}f(D)dD\,.$$

$$\textbf{(Bank's competitive interest setting equation)} \tag{3.7}$$

Again, the first two terms in the retailer's profit expression are together her budget position, B_1 before she makes the loan back payment. The next term is her loan back payment and similar to LIFO, the last term is the $t = 1$ value of her unused budget at the end of t_0.

Finally, we present the case for Full Buy Back financing scheme (FBB for short),. In this case, supplier commits to buy back all unsold items at full value.In FBB, supplier is willing to bear the full risk for downstream demand risk. Similar to two previous cases, the supplier's problem can be written as

$$\max_{w\geq 0}\Pi_s(Q,w) = \max_{w\geq 0}\Big\{\mathbb{E}\big[(w-c_p)Q(1+r_f) - (w+c_b)\big(\tfrac{wQ-B}{w} - \big(D-\tfrac{B}{w}\big)^+\big)^+\big]\Big\}$$

$$\text{s.t.}\quad \Pi_r(Q,w,L) \geq B_0(1+r_f),\ \textbf{(IR)}$$

$$\text{where } L \text{ solves the retailer's optimization problem}$$

$$\text{as given in (3.9). } \textbf{(IC)} \tag{3.8}$$

$$
\begin{aligned}
\max_{Q,l\geq 0}\Pi_r(Q,w,l) = \quad & \max_{Q,l\geq 0}\Big\{\mathbb{E}\big[p\min\{Q,D\} + w\big(Q-D\big)^+ \\
& \qquad - \min\{l(1+r_{bf}), B_1\} + (B_0 + l - wQ)(1+r_f)\big]\Big\} \\
\text{s.t.}\quad & B_0 + l - wQ \geq 0,\ \textbf{(Retailer's production budget constraint)} \\
& l(1+r_f) = \textstyle\int_0^\infty \min\{l(1+r_{bf}), B_1\} f(D)dD\,. \\
& \qquad\qquad \textbf{(Bank's competitive interest setting equation)}
\end{aligned} \tag{3.9}
$$

The supplier's problem for FBB can be written as

$$
\begin{aligned}
\max_{w\geq 0}\Pi_s(Q,w) = \quad & \max_{w\geq 0}\Big\{\mathbb{E}\big[(w-c_p)Q(1+r_f) - (w+c_b)\big(Q-D\big)^+\big]\Big\} \\
\text{s.t.}\quad & \Pi_r(Q,w,L) \geq B_0(1+r_f),\ \textbf{(IR)} \\
& \text{where } L \text{ solves the retailer's optimization problem} \\
& \text{as given in (3.9). } \textbf{(IC)}
\end{aligned} \tag{3.10}
$$

3.3.2 The First-Best Solution

The benchmark we use for gauging efficiency for all schemes we study is the first-best case, in which the supply chain is integrated and decisions are made centrally. In this scenario, the integrated firm no longer face incentive and budget constraints. The first-best solution then is:

$$
\max_{Q\geq 0}\Pi_{fb} = \max_{Q\geq 0}\{\mathbb{E}[p\min\{Q,D\} - c_pQ(1+r_f)] + B_0(1+r_f)]\}. \tag{3.11}
$$

Solving (3.11), the optimal order quantity for the first best case can be found as

$$Q^*_{fb} = F^{-1}\left(1 - \frac{c_p(1+r_f)}{p}\right). \tag{3.12}$$

Plugging (3.12) back in (3.11), we can obtain the first-best channel profit Π^*_{fb}. Throughout the rest of the paper, we will be using the first-best quantity Q^*_{fb} and surplus Π^*_{fb} as our benchmarks for quantity and surplus under full supply chain efficiency.

3.3.3 Equilibrium Analysis

In this section, we provide equilibrium analysis for the base case as well as four financing schemes displayed above. For the base case, to avoid triviality, we only focus on the equilibrium outcome when the retailer's budget is low. In this case, the retailer's ordering decision is:

$$Q^*_{bc}(w) = \frac{B_0}{w} \tag{3.13}$$

and the supplier's optimal wholesale price w^*_{bc} is the solution to

$$p\left(\frac{B_0}{w^*_{bc}}\big(1 - F(\frac{B_0}{w^*_{bc}})\big) + \int_0^{\frac{B_0}{w^*_{bc}}} Df(D)dD\right) = 0 \tag{3.14}$$

For commercial loan, [12] provides a detailed analysis. The wholesale price and order quantity can be computed as follows: Q_{cl}^* solves

$$\bar{F}(Q_{cl}^*) - Q_{cl}^* f(Q_{cl}^*) - \frac{c_p(1+r_f)}{p} = 0, \tag{3.15}$$

and the optimal wholesale price w_{cl}^* is

$$w_{cl}^* = \frac{p\bar{F}(Q_{cl}^*)}{(1+r_f)}, \tag{3.16}$$

We now present the optimal contract parameters for LIFO buy back and FIFO buy back financing scheme.

Proposition 5 *There exists κ such that when $Var[D] < \kappa$, the following statements hold:*

(i) Under LIFO buy back scheme, given a wholesale price w, the optimal order quantity $Q_{lf}^*(w)$ satisfies

$$p(1 - F(Q)) + wF\left(Q - \frac{B_0}{w}\right) - w(1+r_f) = 0.$$

The optimal wholesale price w_{lf}^* is the solution to

$$Q_{lf}^*(w)(1+r_f) + (w - c_p)\tfrac{dQ_{lf}^*(w)}{dw}(1+r_f) + \int_0^{Q_{lf}^*(w) - \frac{B_0}{w}} Df(D)dD$$
$$-(Q_{lf}^*(w) + w\tfrac{dQ_{lf}^*(w)}{dw} + c_b(\tfrac{dQ_{lf}^*(w)}{dw} + \tfrac{B_0}{w^2}))F(Q_{lf}^*(w) - \tfrac{B}{w}) = 0,$$

and the optimal order quantity is $Q_{lf}^*(w_{lf}^*)$.

(ii) Under FIFO buy back scheme, given a wholesale price w, the optimal order

quantity $Q^*_{ff}(w)$ *satisfies*

$$Q^*_{ff}(w) = F^{-1}(1 - \frac{wr_f}{p-w}),$$

The optimal wholesale price w^*_{ff} *is the solution to*

$$Q^*_{ff}(w)(1+r_f) + (w-c_p)\tfrac{dQ^*_{ff}(w)}{dw}(1+r_f) + \int_{\frac{B_0}{w}}^{Q^*_{ff}(w)} Df(D)dD$$
$$-\left(Q^*_{ff}(w) + (w+c_b)\tfrac{dQ^*_{ff}(w)}{dw}\right) F(Q^*_{ff}(w)) = 0,$$

and the optimal order quantity is $Q^*_{ff}(w^*_{ff})$.

(iii) Under Full buy back scheme, given a wholesale price w*, the optimal order quantity* $Q^*_{bf}(w)$ *satisfies*

$$Q^*_{bf}(w) = F^{-1}(1 - \frac{wr_f}{p-w}),$$

The optimal wholesale price w^*_{bf} *is the solution to*

$$Q^*_{bf}(w)(1+r_f) + (w-c_p)\tfrac{dQ^*_{bf}(w)}{dw}(1+r_f) + \int_0^{Q^*_{bf}(w)} Df(D)dD$$
$$-\left(Q^*_{bf}(w) + (w+c_b)\tfrac{dQ^*_{bf}(w)}{dw}\right) F(Q^*_{bf}(w)) = 0,$$

and the optimal order quantity is $Q^*_{bf}(w^*_{bf})$.

Utilizing Proposition 5, we can numerically compare the equilibrium outcome and the efficiency of the buy-back financing schemes to those of the base case and the commercial loan. Figure 3.1 presents these results. As can be seen from Figure

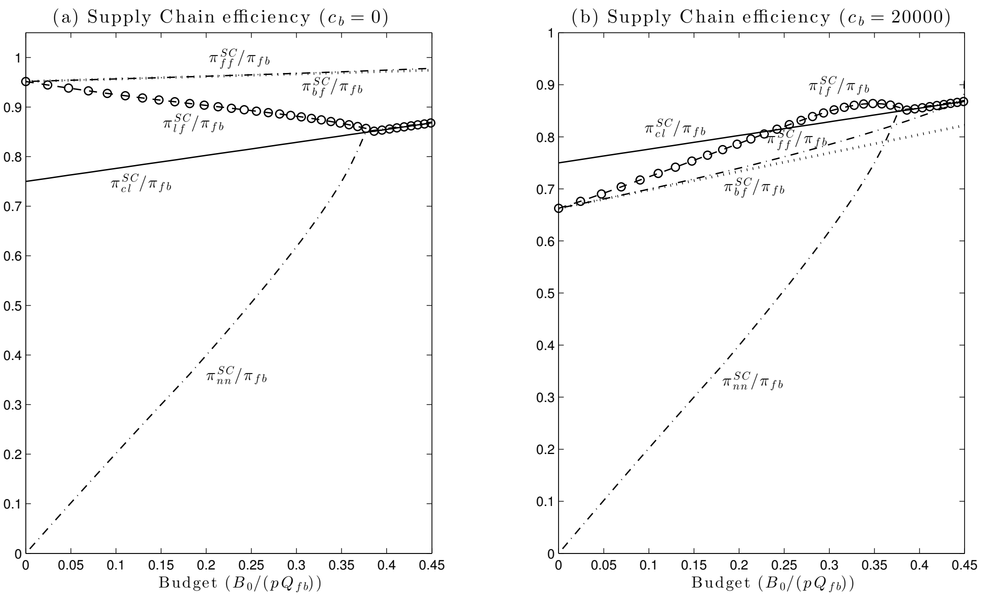

Figure 3.1: Comparison of the supply chain efficiency at equilibrium for base case and financing through Commercial Loans, Full buy back, LIFO buy back and FIFO buy back. For the numerical analysis, the parameter values are c_p=10000, p=100000, r_f=0.06, and the demand follows a uniform distribution in $[0, 100]$.

3.1 panel (a) that, when the buy back cost is low, all buy back financing schemes out perform base case and commercial loan. When the buy back cost is low, the benefits from the buy back agreement dominate. This is also the reason that makes FIFO buy back finance perform the best among all three variants of buy back financing schemes. When $B_0 = 0$, all three buy back financing schemes are the same as retailer's purchase is solely supported by his borrowed money, e.g. every product is on loan. However, as the retailer's budget increases, FIFO prevails as the risk committed by the supplier would induce a order quantity that is the closest to the optimal quantity under the first best scenario. However, panel (b) illustrates that buy back financing, especially FIFO and FBB, may not be the optimal option when buy back cost is relatively high. This is intuitive since product return will impose high costs on the supplier and it's therefore not optimal to buy back as many. Thus, LIFO could perform the best under high buy back cost. To sum, Figure 3.1 indicates that the performance of each buy back financing scheme is heavily affected by the buy back cost. Our goal next is to identify the buy back cost from data and verify the insights obtained from our models.

3.4 Empirical Analysis

We now present the empirical results by applying our theoretical findings established in section 3.3 to the data, which is obtained from Foton Motor, a leading car manufacture in China who designs and manufactures trucks and buses. The company offers buy back financing scheme to ease the financial constraints for its dealers. In this section, we test the efficiency of such financing scheme.

3.4.1 Data

The data sourced from Foton includes quarterly transaction data and data on financing service for all 434 dealers of Foton during 2013 and 2014. The transaction data reports the truck model, body type, quarterly order quantity, quarterly sales and wholesale price. Among all 434 suppliers, 89 and 107 of them have used the buy back financing service in 2013 and 2014, respectively. The data on financing service documents the borrowing amount, credit limit, commission fee as well as the interest rate for each dealer. Table 3.4.1 shows the summary statistics of variables that are used in the specification we discuss below.

Year	Quarter	Order Quantity	Sales	Wholesale	Model
2013	1	8.7712	4.1212	246536.5	4
2013	2	6.6447	5.5844	263096.8	4
2013	3	7.7845	5.1256	257843.1	4
2013	4	8.3201	6.0379	254237.3	4
2014	1	9.1670	4.8460	222547.5	4
2014	2	4.1382	6.2357	228149.7	4
2014	3	3.5051	4.7785	185418.9	4
2014	4	5.4714	5.8384	238054.2	4

3.4.2 Empirical Strategy

In order to examine the effectiveness of the LIFO financing scheme and compare it to other financing schemes such as commercial loan and FIFO buy back financing, we conduct a counterfactual analysis with equilibrium outcomes as our theoretical foundation. To pave way for parameter estimation and the following efficiency analysis, we start by estimating and uncensoring demand using Expectation-Maximization Algorithm. We then discuss the identification strategy, and, with the demand distribution for each SKU estimated, we jointly estimate the retailer's margin, supplier's margin, buy back cost as well as supplier's forecast error by performing a nonlinear least square estimation on the equilibrium expressions under LIFO buy back financing scheme. Finally, by employing the demand distribution and the calibrated parameters, we explore the impact of LIFO buy back financing scheme on channel profit and contrast it to other financing schemes studied in section 3.3.

3.4.3 Estimation

3.4.3.1 Demand Estimation

We model the demand as

$$\log(D_{ij}) = \alpha_0 + \alpha_1 \log(p_{ij}) + \sum_{j=2}^{4} \alpha_j I_{\{M=j\}} + \boldsymbol{X_{ij}}\beta + \epsilon_{ij}\ , \tag{3.17}$$

where ϵ_{ij}s are i.i.d. normally distributed with mean zero and standard deviation σ. In addition, D_{ij} is the demand for ith transaction for truck model j in the data, a_1 captures the price elasticity, a_2 to a_4 reflect the different popularity for different car model. X_{ij} contains a vector of covariates including quarter, city tier and the truck body type. The retail price for each car model is not observable from the dataset, we thus use wholesale price and retailer's margin for each car model as an approximation for the actual retail price. More specifically, we assume $p_i = w_i(1+\zeta_j^D)$, where ζ_j^D is dealer's margin. Thus, regression 3.17 can be rewritten as:

$$\log(D_{ij}) = \alpha_0 + \alpha_1 \log(w_{ij}) + \sum_{j=2}^{4} \underbrace{(\alpha_j + \alpha_1 \log(1+\zeta_j^D))}_{\alpha_j\text{'}} I_{\{M=j\}} + \boldsymbol{X_{ij}}\beta + \epsilon_i \tag{3.18}$$

Notice that for the approximation to work and for α_1 to capture the price elasticity of demand, we assume that a perfect pass-through rate. That is, a unit increase in wholesale price for a vehicle with will lead to a unit increase in retail price (Weyl and Fabinger [65]). Therefore we can derive the price elasticity by observing the variation in wholesale price/

Our demand estimation could potentially suffer from endogeneity problem, as dealers may have better knowledge about the local demand shock and then set the price accordingly. To address the endogeneity issue, we adopt Instrumental Variables (IV) approach. With the assumption that wholesale price is proportional to the retail price, a qualified instrumental variable should be correlated with the wholesale price in 2014 and uncorrelated with the error term, which in our setting is the demand shock in 2014. To satisfy both criteria, We use the wholesale price in 2013 as an instrument. Since for trucks sold in 2013 and 2014 with the same model and body type, the wholesale prices in the two years are strongly correlated. Moreover, with seasonality and location controlled, the price in 2013 is uncorrelated with the demand shock in 2014. With the validity of the instrument is checked, we then apply 2SLS to cope with the endogeneity issue.

Another obstacle to overcome is that when a specific car is sold out, it's not recorded in the data how many customers are exposed to the out-of-stock situation, as sales data are censored demand with unfulfilled demand unaccounted for. Thus, similar to Tunca and Zhu [58], we employ an Expectation Maximization(EM) algorithm to recover the censored demand data. Since ϵ_{ij}s are i.i.d. normally distributed with mean zero, the logarithm of demand is normally distributed, and the demand itself follows a lognormal distribution. Regression 3.17 can be summarized by $\log(D_{ij}) = \boldsymbol{Z_{ij}^T}\beta_{EM} + \epsilon_i$, where $\boldsymbol{Z_{ij}}$ is a vector of covariates for model j that includes the fitted value for 2014 wholesale price from the first stage of 2SLS and all other controls that are specified in regression 3.17, β_{EM} is a $K \times 1$ column vector of the coefficients of the regressors that needs to be estimated through EM estimation. For each model j, we define n_j to be the total sample size, where the first m_j observations on sales are not binding, while the rest $n_j - m_j$ entries bind. In addition, denote D_{ij} and $D_{ij(obs)}$ to be the real demand and observed demand, respectively. Given β', the conditional log-likelihood function can be written as

$$\begin{aligned}\mathcal{L}(\beta;\beta',D_{ij}) = -\sum_{j=1}^{4}\frac{n_j}{2}\log(2\pi\sigma_j^2) - \frac{1}{2}\sum_{j=1}^{4}\sum_{i=1}^{m_j}\frac{(\log(D_{ij}) - \boldsymbol{Z_{ij}^T}\beta_{EM})^2}{\sigma_j^2} \\ - \frac{1}{2}\sum_{j=1}^{4}\sum_{i=m_j+1}^{n_j}\frac{(\mathbb{E}[\log(D_{ij})|\beta', D_{obs(ij)}] - \boldsymbol{Z_{ij}^T}\beta_{EM})^2}{\sigma_j^2}.\end{aligned} \tag{3.19}$$

The results for EM estimation is presented in Table 3.2. With the coefficients of the regressor estimated, we can calculate the demand distribution as follows. First, the mean of the logarithm of uncensored demand for each transaction can be derived by $\mu_{ij} = \boldsymbol{Z_{ij}^T}\beta_{EM}$. In addition, the variance for individual transaction can be derived from the variance of the sample under the assumption that the variance for each transaction is proportional to the mean of the logarithm of uncensored demand, i.e. $\sigma_{ij}^2 = \sigma_j^2(\mu_{ij}/\sum_{k=1}^{N}\mu_{kj})$.

3.4.4 Structural Estimation

The retail price p and production cost c_p for each truck are crucial for calculating the supply chain efficiency under various financing schemes. However, p and c_p are not available in the dataset. In order to conduct efficiency analysis we

Table 3.2: EM Estimation Outcomes for Demand Distributions

	Estimate	Std. Error
Intercept	5.1857^{***}	1.433
Quarter2	0.0392^{*}	0.0335
Quarter3	$-\ 0.1283^{***}$	0.0373
Quarter4	-0.0109	0.0379
City_Tier2	0.0160	0.0597
City_Tier3	0.0726	0.0593
City_Tier4	0.0277	0.0605
Car_Body2	0.2059^{**}	0.0899
Car_Body3	0.4991^{***}	0.1004
Car_Body4	0.4763^{***}	0.1068
Car_Model2	-0.2156^{***}	0.0407
Car_Model3	-0.4214^{***}	0.1005
Price_IV	$--0.3483^{***}$	0.1191

p<0.01 ***, p<0.05 **, p<0.1 *

need to calibrate these underlying parameters by performing structural estimation. Estimating p and c_p for each individual truck would lead to unrealistic outcomes, we instead calibrate the model specific profit margin for both car dealer and car manufacture. We denote ζ_j^D as the dealer's profit margin for model j and ζ_j^M as the manufacture's.

As shown in the figure 3.1, the effectiveness of any buy back financing scheme is greatly affected by the magnitude of the buy back cost. Therefore, besides retail price and production cost, we also estimate supplier's buy back cost. In specific, we decompose the buy back cost c_b by defining $c_b = c_{b(dist)} + c_{b(fix)}$. $c_{b(dist)}$ captures the per distance cost, which includes the labor cost, toll fee and gas price, and $c_{b(fix)}$ is the fixed cost for processing the each returned truck.

Also, due to the ever-changing economic environment in China, the demand for automobiles tend to be difficult to forecast. As a result, the demand forecasts used by retailers to make ordering decisions tend to deviate from the real demand distribution. Thus, we also include forecast errors in our structural estimation. Due to different economic environment as well as varying target customers, companies usually have separate demand forecasts for different regions as well as different car model. We therefore let ξ_k^R capture the forecast error for each dealer in province k and ξ_j^M as the forecast error for model j. In what follows, we denote $f_{\mu,\sigma}$ and $F_{\mu,\sigma}$ to be the p.d.f. and c.d.f. of the log-normal demand variable with mean μ and standard deviation σ. When forecast error is considered, the p.d.f. and c.d.f. for the log demand random variable for transaction i for car model j in province k are therefore $f_{\{\mu_{ijk}(1+\xi_k+\kappa_j),\sigma^2_{ijk}\}}$ and $F_{\{\mu_{ijk}(1+\xi_k+\kappa_j),\sigma^2_{ijk}\}}$.

Let Z be the number of province in the data, N_k be the total types of model sold in province k, and M_{jk} be the number of observations of model j in province k. We assume that both the dealer and the manufacture behave rationally when setting wholesale price and deciding order quantity. Hence, we perform a Nonlinear Least Square on the equilibrium expressions for LIFO, i,e, Proposition 5 part (i) to calibrate the dealer's and manufacture's profit margin as well as the regional forecast error.

$$\min_{\zeta_j^D,\zeta_j^M,\xi_k^R,\xi_j^M,c_b}\Bigg\{\sum_{k=1}^{Z}\sum_{j=1}^{N_k}\sum_{i=1}^{M_{jk}}\Bigg(w_{ijk}(1+\zeta_j^D)(1-F_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}))$$

$$+w_{ijk}\big(F_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}-\tfrac{B_{ijk}}{w_{ijk}})-(1+r_f)\big)\Bigg)^2$$

$$+\sum_{k=1}^{Z}\sum_{j=1}^{N_k}\sum_{i=1}^{M_{jk}}\Bigg(Q_{ijk}(1+r_f)+w_{ijk}\zeta_j^M\phi_{ijk}(1+r_f)+\nu_{ijk}$$

$$-(Q_{ijk}+w_{ijk}\phi_{ijk}$$

$$+c_b(\phi_{ijk}+\tfrac{B_0}{w_{ijk}^2}))F_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}-\tfrac{B_{0ijk}}{w_{ijk}})\Bigg)^2\Bigg\},$$

where

$$B_{ijk} = w_{ijk}Q_{ijk}-L_{ijk} \tag{3.20}$$

$$\nu_{ijk} = \int_0^{Q_{ijk}-\frac{B_{0\{ijk\}}}{w_{ijk}}} Df_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(D)dD \tag{3.21}$$

$$\phi_{ijk} = \frac{\mathrm{d}Q_{ijk}}{\mathrm{d}w_{ijk}} \tag{3.22}$$

$$= \frac{-w_{ijk}f_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}-\frac{B_{0ijk}}{w_{ijk}})\frac{B_{ijk}}{w_{ijk}^2}+F_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}-\frac{B_{0ijk}}{w_{ijk}})-(1+r_f)}{-(w_{ijk}(1+\zeta_j^D))f_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk})+w_{ijk}f_{\{\mu_i(1+\xi_k^R+\xi_j^M),\sigma_i^2\}}(Q_{ijk}-\frac{B_{0ijk}}{w_{ijk}})}$$

We calibrate margins of interests and buy back costs under regional as well as model-specific forecast errors. The regional and model-specific forecast errors are in additive form, yet we are still able to identify each of them. Intuitively, if the number of linear simultaneous equations equal to the number unknowns, each unknown can be exactly derived. In the nonlinear setting, since there are far more number of equations than unknowns, and that there are enough variations in the wholesale price as well as in the order quantity, we are able to identify each forecast error, let along the buy back costs and margins. With the identification problem addressed, we now present the estimation results in Table 3.3.

Table 3.3: Results for the NLS Regression for Parameter Estimation

Dealer's Margin	Estimate	Std Error	Manufacturer's Margin	Estimate	Std Error
ζ_1^D	0.0889***	5.1075×10^{-11}	ζ_1^M	0.1073***	2.7419×10^{-9}
ζ_2^D	0.1186***	4.3442×10^{-7}	ζ_2^M	0.1859***	2.6768×10^{-9}
ζ_3^D	0.1486***	2.4713×10^{-7}	ζ_3^M	0.1227***	1.0446×10^{-5}
Regional Forecast Error	Estimate	Std Error		Estimate	Std Error
Region1	-0.0910***	1.4450×10^{-7}	Region15	0.0789***	4.8310×10^{-6}
Region2	-0.3382***	5.3996×10^{-8}	Region16	0.0716***	1.3479×10^{-6}
Region3	0.3293***	2.9395×10^{-7}	Region17	-0.0046***	1.7620×10^{-6}
Region4	0.2499***	4.5968×10^{-6}	Region18	0.3584***	3.3334×10^{-6}
Region5	0.2827***	1.9377×10^{-6}	Region19	-0.1650***	1.9012×10^{-6}
Region6	-0.1868***	2.0264×10^{-6}	Region20	0.1208***	2.2470×10^{-6}
Region7	0.3032***	2.7711×10^{-5}	Region21	0.3046***	3.5137×10^{-7}
Region8	0.3367***	6.4689×10^{-6}	Region22	-0.2728***	1.1512×10^{-6}
Region9	0.2100***	5.6848×10^{-6}	Region23	0.1457***	3.2405×10^{-6}
Region10	0.0132***	5.0917×10^{-7}	Region24	-0.1079***	4.3648×10^{-6}
Region11	0.0546***	5.9060×10^{-6}	Region25	-0.0738***	2.0166×10^{-6}
Region12	-0.0121***	8.5444×10^{-8}	Region26	-0.3342***	6.1386×10^{-8}
Region13	0.2429***	1.8652×10^{-5}	Region27	0.3468***	2.0586×10^{-6}
Region14	0.3570***	9.1306×10^{-9}	Region28	0.0333***	4.8121×10^{-6}
Model-Specific Forecast Error	Estimate	Std Error			
Model1	0.3636***	1.5634×10^{-7}			
Model2	-0.1967***	2.6375×10^{-6}			
Model3	-0.1281***	2.6618×10^{-7}			
Buy Back Cost Per km(Yuan)	Estimate	Std Error			
$c_{b(dist)}$	5.9166***	5.7115×10^{-6}			
$c_{b(fix)}$	160.0752***	4.3531×10^{-4}			
Number of Observations:	2561				

$p<0.01$ ***, $p<0.05$ **, $p<0.1$*

As can be seen from the table, dealer's average margin is around 12%, and supplier enjoys on average 13% margin, which is consistent with the 10% average margin shown in Foton Motor's 2014 annual report. The forecast errors range from −33% to 36%. Most notably, $c_{b(dist)}$ is 5.9 Yuan/km or equivalently 1.4 \$/mile. Since Foton's factories and warehouses locate at Beijing, the distance we used is the average distance from each province to Beijing. Moreover, $c_{b(fix)}$ is estimated to be 160 Yuan or 14 dollars equivalently. The 160\$ could be explained by the extra handling cost for Foton after the vehicle arrives at Beijing. Following the formula for computing the total return cost, $c_b = c_{b(dist)} + c_{b(fix)}$, the total return cost is calculated and plotted in Figure 3.2. We can see from Figure 3.2 that, according to our estimation, buying back a vehicle from Tibet could cost as much as 23000 Yuan due to its remoteness from Beijing. In the meantime, it only takes 160 Yuan to return a vehicle from a dealer who locates at Beijing thanks to its proximity to the warehouse.

3.4.5 Counterfactual Analysis

Now that we obtain the forecast errors, buy back cost along with average gross margin of each car model for both dealer and manufacturer, we are able to examine the performance of all the financing schemes studied in section 3.3. More specifically, using the estimation results as well as the data, we first calculate what the optimal order quantity and the optimal wholesale would be had Foton implemented other financing schemes in 2014. We then plug in the calculated parameters to calculate

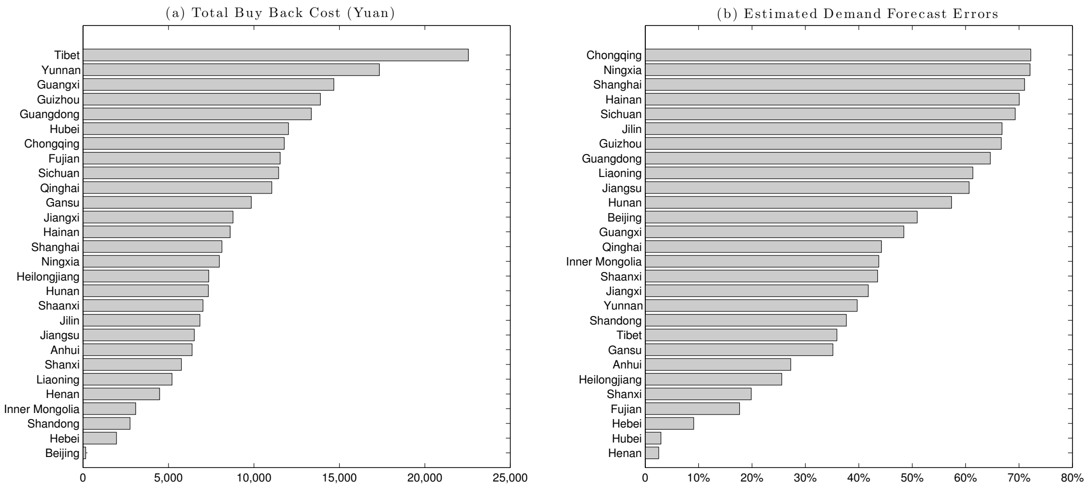

Figure 3.2: Nonlinear Least Square Estimation Results. Panel (a) shows the total buy back cost needed for buying back one vehicle from each province. Panel (b) shows the estimated regional forecast errors for 2014

the supply chain efficiency, formally written as

$$\text{Efficiency} = \frac{\pi_r(Q_i^*, w_i^*, \boldsymbol{\theta}) + \pi_s(Q_i^*, w_i^*, \boldsymbol{\theta})}{\pi_{fb}(Q_{fb}^*, w_{fb}^*, \boldsymbol{\theta})} \tag{3.23}$$

we aim to study the supply chain profit under each financing scheme. The results are presented in Table 3.4.

Table 3.4: Results for the NLS Regression for Parameter Estimation

	Quantity	Wholesale Price	Efficiency	Estimated Improvement
Base Case	0.4500	302295.0	0.4554	-
Commercial Loan	0.8347	298674.4	0.7890	73.25%
LIFO	1.2801	303300.0	0.8004	75.76%
FIFO	1.4128	319532.9	0.7518	65.08%
Full Buy Back	1.4229	319994.6	0.7424	63.02%

Table 3.4 indicates that first, LIFO buy back financing scheme can significantly improve upon the base case scenario in which dealer is not supported by external

capital or buy back contract. Moreover, both FIFO and Full Buy Back schemes are inferior to LIFO Buy Back scheme. The underlining reason is that although buying back unsold vehicles is not too costly, FIFO and FBB induce too high a stock level when demand forecast errors are positive and large. That is to say, LIFO's superiority lies in its robustness under large positive demand bias and its being less affected by the buy back costs. This could be the reasons that make LIFO the most commonly used buy back financing scheme in the industry.

We can also see from Table 3.4 that the FIFO Buy Back scheme performs better than the Full Buy Back one. This is because buying back unsold products at full wholesale price will not coordinate the supply chain, and buying back everything at full wholesale price may be less optimal than buying back a proportion of the total unsold products. In practice, it's also not feasible to implement the optimal buy back contract which could potentially coordinate the supply chain, as the purpose of such buy back financing scheme is not only to induce the dealer to place a higher order quantity, but more importantly, to ensure bank that the dealer will be able to pay back the loan under various demand realization. To set the buy back price lower than the wholesale price may render the dealer insolvent under bleak demand.

3.5 Discussion and Conclusion

We illustrate a innovative financing scheme in which the supplier commits to buy back unsold products that are on loan to help dealer secure finance and mitigate downstream demand risk. We model the LIFO buy back financing scheme together with other variants of LIFO buy back scheme through a game-theoretic setup. We futher tie our model to the data obtained from a Chinese automotive manufacturer to calibrate model parameters as well as gauge the efficiency gain from different buy back financing schemes.

Numerical analysis suggests that buy back financing schemes perform significantly better than the base case scenario in which the retailer is not supported by bank or supplier. However, the efficiency of each buy back financing is contingent on the cost of buying back unsold product. Buy back cost would be less of a concern for non-fragile products of small volume, yet buying back large-volume products such as vehicles tends to be costly. Thus, the effectiveness of such buy back financing scheme is likely to vary across industry and should be brought under scrutiny with the help of information from the data. A future research direction could therefore be to conduct a cross-industry analysis to examine the usefulness in each industry.

Our empirical analysis suggests that LIFO buy back scheme could significantly improve the supply chain efficiency compared to the base case, and its performance is superior to that for FIFO and Full Buy Back financing schemes. Admittedly, retailer has less incentive to stock under LIFO, yet it makes LIFO less likely to deviate to much from the first best stocking level when demand is overestimated. A possible avenue for future research could be to examine LIFO's performance when the downstream demand is underestimated, or when the demand forecast errors have mixed signs. The insights obtained from our study and future follow up studies would contribute to the understanding of the novel financing schemes and could also shed light on the potential improvements for such schemes.

Appendix A: Appendix for Essays on Supply Chain Finance

Table A.1: Model Notation for Section 3.3

w:	Unit wholesale price for the product
Q:	Retailer's order quantity
D:	Consumer demand
F, f:	c.d.f. and p.d.f. for D
F_R, f_R:	c.d.f. and p.d.f. for $w \cdot D$
p:	Unit retail price for the product
c_p:	Supplier's unit production cost
c_g:	Retailer's unit goodwill loss cost
c_e:	Retailer's unit processing and shipping cost for returned products
r_f:	Risk-free interest rate
δ_{bi}:	Bank's discount rate on the loan for BIF
B_0:	Supplier's initial cash position at $t = 0$
B_1:	Supplier's cash position before paying the bank loan at $t = 1$
L:	The supplier's selected loan amount
Π_r:	Retailer's expected ending net profit at time $t = 1$
Π_s:	Supplier's expected ending net profit at time $t = 1$
a_l:	The defect probability of the supplier's product for a high quality supplier
a_h:	The defect probability of the supplier's product for a low quality supplier
a_n:	The return rate of non-defective products by the consumers
π_l:	Ex-ante probability of the supplier's product having a low defect rate
η_a:	Ex-ante overall defect rate of the supplier's product
ρ:	$(1 + r_f)/(1 - \eta_a)$

A.1 Proofs of Propositions

Proof of Proposition 1: We will present the proof only for the commercial loan case. The proofs for the buyer intermediated financing scheme for this proposition will be similar and hence be omitted. By backwards induction, we first solve the bank's competitive interest rate setting problem for any given positive $Q, w, l > 0$. Define

$$G(l, r_{cl}) = (1-\eta_a)\mathbb{E}[\min\{l(1+r_{cl}), (B_0 + l - c_pQ)(1+r_f) + w\min\{Q, D\}\}] \\ + \eta_a \min\{l(1+r_{cl}), (B_0 + l - c_pQ)(1+r_f)\} - l(1+r_f)\,. \quad \text{(A.1)}$$

By (2.3), the bank sets the interest rate r_{cl}^* by solving

$$G(l, r_{cl}) = 0. \quad \text{(A.2)}$$

Notice that for any fixed $l \geq 0$, $G(l, r_{cl})$ is strictly increasing in r_{cl} for $l(1+r_{cl}) < (B_0 + l - c_pQ)(1+r_f) + wQ$, and equals $(B_0 - c_pQ)(1+r_f) + (1-\eta_a)w\mathbb{E}[\min\{Q, D\}]$ for $l(1+r_{cl}) \geq (B_0 + l - c_pQ)(1+r_f) + wQ$.

When $B_0 \geq c_pQ$, then $l(1+r_f) \leq (B_0 + l - c_pQ)(1+r_f)$, and hence $G(l, r_{cl})|_{r_f = r_{cl}} = 0$. That is, for any $B_0 \geq c_pQ$, $r_{cl}^* = r_f$ is a solution to (A.2), and since $l(1+r_f) < (B_0 + l - c_pQ)(1+r_f) + wQ$, $G(l, r_{cl})$ is strictly increasing in r_{cl} at $r_{cl} = r_f$ and is non-decreasing everywhere, it is the unique solution. When $B_0 < c_pQ$, plugging in $r_{cl} = r_f$, since $\eta_a > 0$, we obtain

$$\begin{aligned} G(l, r_f) &= (1-\eta_a)\mathbb{E}[\min\{l(1+r_f), (B_0 + l - c_pQ)(1+r_f) + w\min\{Q, D\}\}] \\ &\quad + \eta_a \min\{l(1+r_f), (B_0 + l - c_pQ)(1+r_f)\} - l(1+r_f) \\ &< (1-\eta_a)l(1+r_f) + \eta_a l(1+r_f) - l(1+r_f) = 0. \end{aligned} \quad \text{(A.3)}$$

It then follows that since $G(l, r_{cl})$ is strictly increasing for $l(1+r_{cl}) < (B_0 + l - c_pQ)(1+r_f) + wQ$, when $B_0 < c_pQ$, (A.2) will have a unique solution, r_{cl}^* in $(r_f, ((B_0 + l - c_pQ)(1+r_f) + wQ)/l - 1)$, if and only if $(B_0 - c_pQ)(1+r_f) + (1 - \eta_a)w\mathbb{E}[\min\{Q, D\}] > 0$. Otherwise, if $(B_0 - c_pQ)(1+r_f) + (1-\eta_a)w\mathbb{E}[\min\{Q, D\}] = 0$, then all $r_{cl} \geq ((B_0 + l - c_pQ)(1+r_f) + wQ)/l - 1$ will be a solution, and if $(B_0 - c_pQ)(1+r_f) + (1-\eta_a)w\mathbb{E}[\min\{Q, D\}] < 0$, then there will be no solution.

To summarize, when $(B_0 - c_pQ)(1+r_f) + (1-\eta_a)w\mathbb{E}[\min\{Q, D\}] > 0$, we have

$$r_{cl}^* = \begin{cases} r_f, & \text{if } B_0 \geq c_pQ \\ r_{cl} \in (r_f, ((B_0 + l - c_pQ)(1+r_f) + wQ)/l - 1) \text{ that solves (A.2)}, & \text{if } B_0 < c_pQ\,. \end{cases} \tag{A.4}$$

Now, to solve (2.3), notice that, when the supplier determines the loan amount l, how much he chooses to borrow affects the bank's interest rate, as determined by the bank's competitive interest setting equation in (2.3), r_{cl}^* is a function of l. Further, when $(B_0 - c_pQ)(1+r_f) + (1-\eta_a)w\mathbb{E}[\min\{Q, D\}] > 0$, $G(l, r_{cl})$ has continuously differentiable partial derivatives in l and r_{cl}, which implies by the implicit function theorem that $r_{cl}^*(l)$ is continuously differentiable in l. Therefore, in this region, taking the total derivative of the supplier's objective function as given in (2.2),

$$\frac{d\Pi_s^{cl}(l, r_{cl}^*(l))}{dl} = \frac{\partial \Pi_s^{cl}(l, r_{cl}^*(l))}{\partial l} + \frac{\partial \Pi_s^{cl}(l, r_{cl}^*(l))}{\partial r_{cl}^*}\frac{dr_{cl}^*(l)}{dl}\,. \tag{A.5}$$

When $B_0 \geq c_pQ$, from (A.4) we have $r_{cl}^*(l) = r_f$ for all $l \geq 0$. By (2.2), we can then see that $\Pi_s^{cl}(l, r_{cl}(l))$ is independent of l, and hence $d\Pi_s^{cl}/dl = 0$. When $B_0 < c_pQ$, defining

$$D^* = \frac{l(r_{cl} - r_f) + (c_p Q - B_0)(1 + r_f)}{w}\,, \tag{A.6}$$

and again applying the implicit function theorem to (A.1), we have

$$\frac{dr^*_{cl}(l)}{dl} = -\frac{\partial G(l, r_{cl})/\partial l}{\partial G(l, r_{cl})/\partial r_{cl}}\bigg|_{r_{cl}=r^*_{cl}(l)} = -\frac{(1-\eta_a)\bar{F}(D^*)(r^*_{cl}(l) - r_f)}{(1-\eta_a)\bar{F}(D^*)l} = \frac{(r_f - r^*_{cl}(l))}{l}\,. \tag{A.7}$$

In addition, from (2.2), we have

$$\frac{\partial \Pi^{cl}_s(l, r^*_{cl}(l))}{\partial l} = (1-a_l)(r_f - r^*_{cl}(l))F(D^*), \text{ and } \frac{\partial \Pi^{cl}_s(l, r^*_{cl}(l))}{\partial r_{cl}} = -(1-a_l)lF(D^*)\,. \tag{A.8}$$

By plugging (A.7) and (A.8) into (A.5), we then have

$$\frac{d\Pi^{cl}_s(l, r^*_{cl}(l))}{dl} = (1-a_l)(r_f - r^*_{cl}(l))F(D^*) - (1-a_l)lF(D^*)\frac{(r_f - r^*_{cl}(l))}{l} = 0\,. \tag{A.9}$$

That is, given the bank's response in setting the interest rate competitively, the supplier is indifferent about the loan amount he receives for $B_0 < c_p Q$ as well as for the case $B_0 \geq c_p Q$. Note that the supplier also has to satisfy the production budget constraint in (2.3), therefore, the loan borrowed has to be sufficient to cover the production cost, i.e., $l \geq (c_p Q - B_0)^+$. However, if the supplier borrows more than needed, he will invest the excess amount $l - (c_p Q - B_0)^+$ in the risk-free asset and pay it back to the bank without improving his objective function, i.e., the borrowing to lend the money will be a trivial action. Therefore, the only amount the supplier can borrow to cover its production costs without any trivial borrowing and lending is when $L = (c_p Q - B_0)^+$.

In order to solve the retailer's optimization problem, (3.10), first consider the case $B_0 \geq c_p Q$. As we have shown above, in this case $L = 0$. Then the supplier's IR constraint in (3.10) becomes

$$(B_0 - c_p Q)(1 + r_f) + (1 - a_l)(wQ - w\mathbb{E}[(Q - D)^+]) \geq B_0(1 + r_f)\,. \tag{A.10}$$

Notice that the left hand side of (A.10) is increasing in w. However, again from (3.10), we have

$$\frac{\partial \Pi_r^{cl}(Q, w)}{\partial w} = (1 - a_l)(\mathbb{E}[(Q - D)]^+ - Q) < 0, \tag{A.11}$$

which means that the retailer's profit is decreasing in w. Therefore, for any given $Q \geq 0$, in the optimal solution (A.10) must be binding. Thus, solving for w and plugging in $\Pi_r^{cl}(Q, w)$, the retailer's profit function on $B_0 \geq c_p Q$ then is

$$\Pi_r^1(Q) \triangleq ((1-a_l)((1-a_n)p-a_n c_e)-a_l c_e)\mathbb{E}\left[\min\{Q, D\}\right]-c_g\mathbb{E}[(D-Q)^+]-c_p Q(1+r_f)\,. \tag{A.12}$$

Also note that,

$$\frac{d^2\Pi_r^1(Q)}{dQ^2} = -((1 - a_l)((1 - a_n)p - a_n c_e) - a_l c_e + c_g)f(Q) < 0, \tag{A.13}$$

since $(1 - a_l)((1 - a_n)p - a_n c_e) - a_l c_e > 0$. Therefore $\Pi_r^1(Q)$ is concave and, by solving the first order condition, is maximized at

$$Q = Q^*_{fb} = F^{-1}\left(1 - \frac{c_p(1+r_f)}{(1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g}\right). \quad (A.14)$$

Next, suppose $B_0 < c_p Q$, then the supplier will borrow $L = c_p Q - B_0$ and his participation constraint in (3.10) will be

$$(1-a_l)(w\mathbb{E}[\min\{Q, D\}] - \mathbb{E}[\min\{L(1+r_{cl}), w\min\{Q, D\}\}]) \geq B_0(1+r_f). \quad (A.15)$$

Further, from the bank's interest rate setting equation,

$$\frac{L(1+r_f)}{(1-\eta_a)} = \mathbb{E}[\min\{L(1+r_{cl}), w\min\{Q, D\}\}]. \quad (A.16)$$

Once again, since the retailer's objective function is decreasing in w, (A.15) must be binding in optimality. Therefore by plugging (A.15) and (A.16) in Π_r^{cl}, the retailer's profit function on $B_0 < c_p Q$ is

$$\begin{aligned}\Pi_r^2(Q) \triangleq\ & ((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e)\mathbb{E}\left[\min\{Q, D\}\right] - c_g\mathbb{E}[(D-Q)^+] \\ & - (c_p Q - B_0)\frac{(1+r_f)(1-a_l)}{1-\eta_a} - B_0(1+r_f). \quad (A.17)\end{aligned}$$

Further, $d^2\Pi_r^2(Q)/dQ^2$ is also as given in (A.13) and is negative. That is, $\Pi_r^2(Q)$ is also concave, and by solving its first order condition, is maximized at

$$Q = \bar{Q}_{cl} \triangleq F^{-1}\left(1 - \frac{c_p(1+r_f)(1-a_l)}{(1-\eta_a)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right). \quad (A.18)$$

In addition, plugging $L = c_pQ - B_0$ in the supplier's IR constraint in (A.15), since (A.15) is binding and by (A.16) we obtain

$$(1 - a_l)(w\mathbb{E}[\min\{Q, D\}] - \frac{(c_pQ - B_0)(1 + r_f)}{(1 - \eta_a)}) = B_0(1 + r_f)\,. \tag{A.19}$$

This means that $(B_0 - c_pQ)(1+r_f) + w\mathbb{E}[\min\{Q, D\}] \geq 0$, i.e., the bank's competitive interest rate setting equation in (2.3) has a solution, confirming the feasibility of $\bar{Q}_{cl}$ for (3.10). Note that

$$\begin{aligned} Q^*_{fb} &= F^{-1}\left(1 - \frac{c_p(1 + r_f)}{(1 - a_l)((1 - a_n)p - a_nc_e) - a_lc_e + c_g}\right) \\ &> F^{-1}\left(1 - \frac{c_p(1 - a_l)(1 + r_f)}{(1 - \eta_a)((1 - a_l)((1 - a_n)p - a_nc_e) - a_lc_e + c_g)}\right) = \bar{Q}_{cl}\,, \end{aligned} \tag{A.20}$$

as stated in the proposition, since $a_l < \eta_a$. Finally,

$$\Pi^1_r\left(\frac{B_0}{c_p}\right) = \Pi^2_r\left(\frac{B_0}{c_p}\right) = B_0(1 + r_f). \tag{A.21}$$

When $B_0/c_p > Q^*_{fb}$, $\bar{Q}_{cl} < Q^*_{fb} < B_0/c_p$, and since Π^2_r is concave, Π^2_r is then decreasing on $Q > B_0/c_p$. Further, again since $B_0/c_p > Q^*_{fb}$, the maximizer Q^*_{fb} of $\Pi^1_r(Q)$ is in $0 \leq Q < B_0/c_p$. Hence $\Pi^{cl}_r(Q^*_{fb}, w^*(Q^*_{fb})) = \Pi^1_r(Q^*_{fb}) > \Pi^1_r(B_0/c_p) = \Pi^2_r(B_0/c_p) > \Pi^2_r(Q) = \Pi^{cl}_r(Q, w^*(Q))$ for any $Q > B_0/c_p$, where, for a given $Q \geq 0$, $w^*(Q)$ is the solution of (A.15). Therefore, we can conclude that if $B_0/c_p > Q^*_{fb}$, the retailer's optimal order quantity is Q^*_{fb} and $L = 0$, i.e., the supplier does not get any loan. The corresponding wholesale price can be obtained as given in (2.14) by solving (A.10) as binding. This proves part (i).

For part (ii), notice that when $\bar{Q}_{cl} < B_0/c_p < Q^*_{fb}$, since $\Pi^1_r(Q)$ is concave and maximized at Q^*_{fb}, $\Pi^1_r(Q)$ is increasing on $0 \leq Q \leq B_0/c_p$, and attains its maximum on this interval at $Q = B_0/c_p$. On the other hand, since $\Pi^2_r(Q)$ is also concave and is maximized at $\bar{Q}_{cl}$, it is decreasing on $Q \geq B_0/c_p$. Since $\Pi^1_r(B_0/c_p) = \Pi^2_r(B_0/c_p)$, and since $\Pi^{cl}_r(Q, w^*(Q)) = \Pi^1_r(Q)$ for $0 \leq Q \leq B_0/c_p$, and $\Pi^{cl}_r(Q, w^*(Q)) = \Pi^2_r(Q)$ for $Q > B_0/c_p$ it follows that $\Pi^{cl}_r(Q, w^*(Q))$ is maximized at $Q^*_{cl} = B_0/c_p$, and the supplier again borrows $L = c_pQ^*_{cl} - B_0 = 0$. Once again plugging this value into the supplier's binding participation constraint, we find that w^*_{cl} satisfies (2.14). ■

Proof of Proposition 2: Suppose $B_0/c_p < \bar{Q}_{cl}$. Then, using the notation of the proof of Proposition 1, since $\bar{Q}_{cl} < Q^*_{fb}$, and by concavity of Π^1_r, $\Pi^1_r(Q)$ is increasing on $0 \leq Q \leq B_0/c_p$ and attains its maximum at $Q = B_0/c_p$. On the other hand, $\Pi^2(Q)$ has its global maximizer $\bar{Q}_{cl}$ in $B_0/c_p > \bar{Q}_{cl}$. Again since, Π^2_r is concave and $\Pi^1_r(B_0/c_p) = \Pi^2_r(B_0/c_p)$, this means that $\Pi^2_r(Q)$ is increasing on $0 \leq Q \leq \bar{Q}_{cl}$ and decreasing for $Q \geq \bar{Q}_{cl}$, i.e., $\Pi^2_r(Q)$ is maximized at $Q^*_{cl} = \bar{Q}_{cl}$. Once again, plugging Q^*_{cl} into into the supplier's binding participation constraint, we obtain w^*_{cl} as given in (2.14). Further, as we have shown in the proof of Proposition 1, the supplier's budget constraint is binding in (2.3), i.e., $L^*_{cl} = c_p\bar{Q}_{cl} - B_0 > 0$ as given in (2.15). Finally, after plugging L^*_{cl} into the bank's interest setting equation (A.16), we have

$$\frac{L^*_{cl}(1+r_f)}{(1-\eta_a)} = \mathbb{E}[\min\{L^*_{cl}(1+r_{cl}), w\min\{Q,D\}\}] \tag{A.22}$$

$$= \int_0^{L^*_{cl}(1+r_{cl})} z f_R(z)dz + L^*_{cl}(1+r_{cl})\bar{F}_R\left(L^*_{cl}(1+r_{cl})\right), \tag{A.23}$$

where the second equality follows from the fact that $\min\{L_{cl}^*(1+r_{cl}), w\min\{Q,D\}\} = L_{cl}^*(1+r_{cl})$ when $wD \geq L_{cl}^*(1+r_{cl})$. From (A.23), we obtain r_{cl}^* as given in (2.16). This completes the proof. ■

Proof of Proposition 3: First, on $Q < B_0/c_p$, the retailer's objective function is again $\Pi_r^1(Q)$ as given in the proof of Proposition 1. For $Q \geq B_0/c_p$, we first derive the retailer's optimal δ_{bi}. We start by examining the supplier's borrowing behavior. Now, from (2.6),

$$\frac{\partial \Pi_s^{bi}(Q, w, \delta_{bi}, l)}{\partial l} = (1+r_f)(1-\delta_{bi}) - (1-a_l)\,, \tag{A.24}$$

and the supplier's profit is non-increasing in l if and only if

$$\delta_{bi} \geq 1 - \frac{1-a_l}{1+r_f}. \tag{A.25}$$

For any $\delta_{bi} \geq 0$ for which (A.25) is not satisfied, supplier will choose to obtain as high a loan as possible, while the retailer's goal is inducing the supplier to borrow no more than the amount needed to cover production, $(c_pQ - B_0)^+$ as stated in (2.7). Therefore, the retailer sets $\delta_{bi} \geq 1 - (1-a_l)/(1+r_f)$ and the supplier will borrow the exact amount to cover his production costs, i.e., $L = (c_pQ - B_0)^+/(1-\delta_{bi})$. Plugging into the retailer's objective in (2.7) and by (2.4), we obtain

$$\Pi_r^{bi}(Q, w, \delta_{bi}) = \mathbb{E}[((1-a_l)((1-a_n)p - a_nc_e - w) - a_lc_e)\min\{Q,D\} - c_g(D-Q)^+] - \frac{a_l(c_pQ - B_0)}{1-\delta_{bi}}. \tag{A.26}$$

For a given solution (Q, w, δ_{bi}), suppose (A.25) is not binding. Then by (A.26), decreasing δ_{bi} increases $\Pi_r^{bi}(Q, w, \delta_{bi})$, while still preventing the supplier from borrowing over $(c_pQ - B_0)/(1 - \delta_{bi})$. Further, again plugging in (2.3),

$$\Pi_s^{bi}(Q, w, \delta_{bi}, l) = (1 - a_l)(w\mathbb{E}\min\{Q, D\} - \frac{a_l(c_pQ - B_0)}{1 - \delta_{bi}}) \tag{A.27}$$

increases. Finally,

$$(1 + r_f)(1 - \delta_{bi}^*) < (1 + r_f)\frac{1 - a_l}{1 + r_f} = 1 - a_l < 1\,. \tag{A.28}$$

That is, by decreasing δ_{bi}, the supplier's IR constraint and the bank's non-negative profit constraint in (2.7) will still be satisfied. Therefore, in the optimal solution (A.25) must be binding, i.e., $\delta_{bi}^* = 1 - (1 - a_l)/(1 + r_f)$ and $L_{bi}^* = (c_pQ - B_0)(1 + r_f)/(1 - a_l)$. Plugging into the supplier's IR constraint, we have

$$w\mathbb{E}[\min\{Q, D\}] - \frac{(c_pQ - B_0)(1 + r_f)}{1 - a_l} \geq B_0\frac{(1 + r_f)}{1 - a_l}\,. \tag{A.29}$$

As the left hand side of (A.29) is increasing in w, and the retailer's objective function in (2.7) is decreasing in w, (A.29) must also bind in optimality. Solving for w, for any given $Q > B_0/c_p$, we obtain

$$w^*(Q) = \frac{c_pQ(1 + r_f)}{(1 - a_l)E[\min\{Q, D\}]}\,. \tag{A.30}$$

Notice that by (A.30)

$$L_{bi}^* = \frac{(c_p Q - B_0)(1+r_f)}{1-a_l} \le \frac{c_p Q(1+r_f)}{1-a_l} \le \frac{c_p Q(1+r_f)}{(1-a_l)E[\min\{Q,D\}]} \cdot Q = w^*(Q)Q\,. \tag{A.31}$$

That is, L_{bi}^* is feasible for the supplier's problem (2.6). Finally, plugging (A.30) in the retailer's objective we obtain

$$\begin{aligned}\Pi_r^{bi}(Q, w^*(Q), \delta_{bi}) = \Pi_r^3(Q) \;\; &\triangleq \;\; \mathbb{E}[((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e)\min\{Q,D\} - c_g(D-Q)^+] \\ &\quad -(c_p Q - B_0)\frac{(1+r_f)}{(1-a_l)} - B_0(1+r_f)\,, \end{aligned} \tag{A.32}$$

on $Q > B_0/c_p$, which is again concave in Q, and has a unique maximum at

$$Q_{bi}^* = \bar{Q}_{bi} = F^{-1}\left(1 - \frac{c_p(1+r_f)}{(1-a_l)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right) < Q_{fb}^*. \tag{A.33}$$

Finally, again notice that as in the proof of Proposition 1, $\Pi_r^1(B_0/c_p) = \Pi_r^3(B_0/c_p)$. Given these, the rest of the proof proceeds in the similar fashion as in the proofs of Proposition 2 and is skipped. ■

Proof of Proposition 4: To see part (i), first, notice that by (2.16), we have

$$\begin{aligned} L_{cl}^* \frac{1+r_f}{1-\eta_a} &= \int_0^{L_{cl}^*(1+r_{cl})} z f_R(z)dz + L_{cl}^*(1+r_{cl})\bar{F}_R\left(L_{cl}^*(1+r_{cl})\right) \\ &< L_{cl}^*(1+r_{cl}^*)F_R\left(L_{cl}^*(1+r_{cl}^*)\right) + L_{cl}^*(1+r_{cl}^*)\bar{F}_R\left(L_{cl}^*(1+r_{cl})^*\right) = L_{cl}^*(1+r_{cl}^*)\,, \end{aligned} \tag{A.34}$$

which implies $1 + r^*_{cl} > (1 + r_f)/(1 - \eta_a)$. Since $1 + r_{bi} = 1/(1 - \delta_{bi})$, by (2.17) we then have

$$1 + r_f < \frac{1 + r_f}{1 - a_l} = 1 + r_{bi} < \frac{1 + r_f}{1 - \eta_a} < 1 + r^*_{cl}, \tag{A.35}$$

since $0 < a_l < \eta_a$. It follows that $r_f < r^*_{bi} < r^*_{cl}$.

For part (ii), first, for the commercial loan case, when the supplier is borrowing a positive amount, by (2.13),

$$F(Q^*_{cl}) = \int_0^{Q^*_{cl}} f(D)dD = 1 - \frac{c_p(1 + r_f)(1 - a_l)}{(1 - \eta_a)((1 - a_l)((1 - a_n)p - a_n c_e) - a_l c_e + c_g)} > 0, \tag{A.36}$$

and the right hand side of (A.36) is independent of $Var[D]$. Now, as $Var[D] \to 0$, for any $D \neq \mathbb{E}[D]$, $f(D) \to 0$. Therefore, $\lim_{Var[D]\to 0} Q^*_{cl} = \mathbb{E}[D]$. Similarly $\lim_{Var[D]\to 0} Q^*_{bi} = \mathbb{E}[D]$ also follows. Further, as $Var[D] \to 0$, $D \xrightarrow{p} \mathbb{E}[D]$ as well, which implies that for $\varphi = cl, bi$,

$$\lim_{Var[D]\to 0} \{Q^*_\varphi - \mathbb{E}[(Q^*_\varphi - D)^+]\} = \lim_{Var[D]\to 0} \mathbb{E}[\min\{Q^*_\varphi, D\}] = E[D]\,. \tag{A.37}$$

Plugging into (2.14) and (2.19), we then have

$$\begin{aligned}\lim_{Var[D]\to 0} (w^*_{cl} - w^*_{bi}) &= \frac{c_p \mathbb{E}[D] \frac{(1+r_f)}{1-\eta_a} - B_0(1 + r_f)(\frac{1}{1-\eta_a} - \frac{1}{1-a_l})}{\mathbb{E}[D]} - \frac{c_p(1 + r_f)}{1 - a_l} \\ &= \frac{(1 + r_f)}{\mathbb{E}[D]}(\frac{1}{1 - \eta_a} - \frac{1}{1 - a_l})(c_p \mathbb{E}[D] - B_0)\,,\end{aligned} \tag{A.38}$$

Notice that since $L^*_{cl} > 0$, if and only if $c_p Q^{cl} < B_0$. Since $\lim_{Var[D]\to 0} Q^*_{cl} = \mathbb{E}[D]$, if $c_p \mathbb{E}[D] < B_0$, there exists $\bar{\kappa} > 0$, such that for all $Var[D] < \bar{\kappa}$, $L^*_{cl} = 0$. Therefore, there exists $\kappa > 0$ such that, if $Var[D] < \kappa$, then $c_p\mathbb{E}[D] > B_0$ must hold, which, by (A.38) and since $\eta_a > a_l$, implies $w^*_{cl} > w^*_{bi}$. This proves part (ii).

To show part (iii), we start by comparing the equilibrium order quantities. When $L^*_{cl}, L^*_{bi} > 0$, by Propositions 2 and 3 and equations (2.10) and (2.11), $Q^*_{cl} < Q^*_{bi}$ if and only if

$$F^{-1}\left(1 - \frac{c_p(1-a_l)(1+r_f)}{(1-\eta_a)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right) \\ < F^{-1}\left(1 - \frac{c_p(1+r_f)}{(1-a_l)((1-a_l)((1-a_n)p - a_n c_e) - a_l c_e + c_g)}\right). \quad \text{(A.39)}$$

Since F^{-1} is monotonically non-decreasing, (A.39) is satisfied if and only if $\eta_a > 1-(1-a_l)^2$.

To see the profit comparisons, by (A.17) and (A.32), we have

$$\Pi_r^{bi}(Q) - \Pi_r^{cl}(Q) = \Pi_r^3(Q) - \Pi_r^2(Q) = (c_p Q - B_0)(1+r_f)\left(\frac{1-a_l}{1-\eta_a} - \frac{1}{1-a_l}\right). \quad \text{(A.40)}$$

If $\eta_a > 1-(1-a_l)^2$, then as we have shown above, $Q^*_{bi} > Q^*_{cl}$, and by concavity of Π_r^2 and Π_r^3, we have $\Pi_r^3(Q^*_{bi}) > \Pi_r^3(Q^*_{cl}) > \Pi_r^2(Q^*_{cl})$. The case for $\eta_a \le 1-(1-a_l)^2$ follows symmetrically. Therefore, we obtain that $\Pi^*_{bi} > \Pi^*_{cl}$ if and only if $\eta_a > 1-(1-a_l)^2$ as stated in the proposition.

Finally, the percentage of the production costs the supplier borrows under the commercial loan is $(c_p Q^*_{cl} - B_0)/c_p Q^*_{cl} = 1 - B_0/c_p Q^*_{cl}$. Similarly, the percentage of the production costs he borrows under the commercial loan is $1 - B_0/c_p Q^*_{bi}$. Since $Q^*_{bi} > Q^*_{cl}$ if and only if $\eta_a > 1-(1-a_l)^2$, it follows that $1-B_0/c_p Q^*_{bi} > 1-B_0/c_p Q^*_{cl}$

if and only if $\eta_a > 1 - (1 - a_l)^2$. This completes the proof. ■

A.2 Derivations of the Distribution Parameter Updates in Demand Estimation

In order to maximize $\mathcal{L}(\theta; \theta', D_{ij})$ at iteration k, writing the first order conditions for $a_j^{(k+1)}$ and $b_j^{(k+1)}$, we have

$$\partial \mathbb{E}[\mathcal{L}(a_j, b_j, \sigma_j^2; \theta'_k, D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}] / \partial a_j = 0, \tag{A.1}$$

and

$$\partial \mathbb{E}[\mathcal{L}(a_j, b_j, \sigma_j^2; \theta'_k, D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}] / \partial b_j = 0. \tag{A.2}$$

By, (3.19), (A.1) and (A.2), we obtain

$$n_j a_j^{(k+1)} + b_j^{(k+1)} \sum_{i=1}^{n_j} log(p_{ij}) = \sum_{i=1}^{m_j} \log(D_{ij}) + \mathbb{E}[\sum_{i=m_j+1}^{n_j} \log(D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}]. \tag{A.3}$$

and

$$\begin{aligned} a_j^{(k+1)} \sum_{i=1}^{n_j} \log(p_{ij}) + b_j^{(k+1)} \sum_{i=1}^{n_j} (\log(p_{ij}))^2 &= \sum_{i=1}^{m_j} \log(D_{ij}) \log(p_{ij}) \\ &+ \mathbb{E}[\sum_{i=m_j+1}^{n_j} \log(D_{ij}) \log(p_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}]. \end{aligned} \tag{A.4}$$

Jointly solving (A.3) and (A.4) for $a_j^{(k+1)}$ and $b_j^{(k+1)}$, we have

$$a_j^{(k+1)} = \frac{h_{j1}^k \sum_{i=1}^{n_j} (\log(p_{ij}))^2 - h_{j2}^k \sum_{i=1}^{n_j} \log(p_{ij})}{n_j \sum_{i=1}^{n_j} (\log(p_{ij}))^2 - \left(\sum_{i=1}^{n_j} \log(p_{ij}) \right)^2}, \tag{A.5}$$

and

$$b_j^{(k+1)} = \frac{n_j h_{j2}^k - h_{j1}^k \sum_{i=1}^{n_j} \log(p_{ij})}{n_j \sum_{i=1}^{n_j} (\log(p_{ij}))^2 - \left(\sum_{i=1}^{n_j} \log(p_{ij}) \right)^2}, \tag{A.6}$$

where

$$h_{j1}^k = \sum_{i=1}^{m_j} \log(D_{ij}) + \sum_{i=m_j+1}^{n_j} \mathbb{E}[\log(D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}], \tag{A.7}$$

and

$$h_{j2}^k = \sum_{i=1}^{m_j} \log(D_{ij}) \log(p_{ij}) + \sum_{i=m_j+1}^{n_j} \log(p_{ij}) \mathbb{E}[\log(D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}]. \tag{A.8}$$

Note that since

$$\frac{\partial^2 \mathbb{E}[\mathcal{L}(a_j, b_j, \sigma_j^2; \theta_k', D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}]}{\partial a_j^2} = -\frac{n_j}{\sigma_j^2} < 0, \tag{A.9}$$

and

$$\frac{\partial^2 \mathbb{E}[\mathcal{L}(a_j, b_j, \sigma_j^2; \theta_k', D_{ij}) | (a_j^{(k)}, b_j^{(k)}, \sigma_j^{2^{(k)}}), D_{obs(ij)}]}{\partial b_j^2} = -\sum_{i=1}^{n_j} \frac{(\log(p_{ij}))^2}{\sigma_j^2} < 0, \tag{A.10}$$

the expected log likelihood function is concave in a_j and b_j, and hence the first order conditions are sufficient for optimality.

Finally, $\sigma_j^{2(k+1)}$ can be derived by a simpler approach. Since the normal distribution falls into the exponential family, the conditional expectations of the moments can be directly substituted for the moments that occur in the expressions obtained for the complete-data maximum likelihood estimators to perform the next iteration. That is, we can replace the sample moments in $\hat{\sigma}^2 = \frac{\sum_{i=1}^{n_j}(\log(D_{ij}))^2}{n_j} - \left(\frac{\sum_{i=1}^{n_j}\log(D_{ij})}{n_j}\right)^2$ by their conditional expectations and obtain $\sigma_j^{2(k+1)}$. It follows that

$$\begin{aligned}\sigma_j^{2(k+1)} &= \frac{\sum_{i=1}^{m_j}(\log(D_{ij}))^2 + \mathbb{E}[\sum_{i=m_j+1}^{n_j}(\log(D_{ij}))^2|(a_j^{(k)}, b_j^{(k)}, \sigma_j^{2(k)}), D_{obs(ij)}]}{n_j} \\ &- \left(\frac{\sum_{j=i}^{m_j}(\log D_{ij}) + \mathbb{E}[\sum_{i=m_j+1}^{n_j}\log(D_{ij})|(a_j^{(k)}, b_j^{(k)}, \sigma_j^{2(k)}), D_{obs(ij)}]}{n_j}\right)^2. \quad \text{(A.11)}\end{aligned}$$

A.3 Identification of Parameters for the Structural Estimation

Our goal is to obtain the moment equations for our structural Non-Linear Least Square estimation given in (2.24), and show that, given the variation of the data, the joint solution to them is identifiable. Define

$$\Omega_{ij} = (1-a_l)((1-a_n)p_{ij} - a_n c_e) - a_l c_e, \quad \text{(A.1)}$$

$$\nu_{ij}^{(12)} = F^{-1}_{(\mu_{ij}^{(12)}(1+\xi_j^{(12)}),\sigma_{ij}^{(12)})}\left(1 - \frac{c_{p(ij)}^{(12)}\rho}{(1-a_l)((1-a_n)p_{ij}^{(12)} - a_n c_e) - a_l c_e + c_g}\right), \quad \text{(A.2)}$$

$$\nu_{ij}^{(13)} = F^{-1}_{(\mu_{ij}^{(13)}(1+\xi_j^{(13)}),\sigma_{ij}^{(13)})}\left(1 - \frac{c_{p(ij)}^{(13)}(1+r_f)/(1-a_l)}{(1-a_l)((1-a_n)p_{ij}^{(13)} - a_n c_e) - a_l c_e + c_g}\right), \quad \text{(A.3)}$$

$$\phi_{ij}^{(12)}(x_{ij}) = \frac{\log(x_{ij}^{(12)}) - \mu_{ij}^{(12)}(1+\xi_j^{(12)})}{\sigma_{ij}^{(12)}}\,, \tag{A.4}$$

and

$$\phi_{ij}^{(13)}(x_{ij}) = \frac{\log(x_{ij}^{(13)}) - \mu_{ij}^{(13)}(1+\xi_j^{(13)})}{\sigma_{ij}^{(13)}}\,. \tag{A.5}$$

Taking the derivative of the objective in (2.24) with respect to each parameter to be estimated, namely c_g, ρ, and for each industry j, $1 \le j \le N$, $\xi_j^{(12)}$ and $\xi_j^{(13)}$, we respectively obtain the following sample moment equations:

$$\begin{aligned}
&\sum_{j=1}^{N}\sum_{i=1}^{M_j^{(12)}} \nu_{ij}^{(12)}\sigma_{ij}^{(12)} e^{\frac{1}{2}\left(\phi_{ij}^{(12)}(\nu_{ij}^{(12)})\right)^2} \frac{c_{p(ij)}^{(12)}\rho}{(\Omega_{ij}+c_g)^2}(Q_{ij}^{(12)} - \nu_{ij}^{(12)}) \\
&\quad + \sum_{j=1}^{N}\sum_{i=1}^{M_j^{(13)}} \nu_{ij}^{(13)}\sigma_{ij}^{(13)} e^{\frac{1}{2}\left(\phi_{ij}^{(13)}(\nu_{ij}^{(13)})\right)^2} \frac{c_{p(ij)}^{(13)}(1+r_f)}{(1-a_l)(\Omega_{ij}+c_g)^2}(Q_{ij}^{(13)} - \nu_{ij}^{(13)}) = 0,
\end{aligned} \tag{A.6}$$

$$\sum_{j=1}^{N}\sum_{i=1}^{M_j^{(12)}} \nu_{ij}^{(12)}\sigma_{ij}^{(12)} e^{\frac{1}{2}\left(\phi_{ij}^{(12)}(\nu_{ij}^{(12)})\right)^2} \frac{c_{p(ij)}^{(12)}}{\Omega_{ij}+c_g}(Q_{ij}^{(12)} - \nu_{ij}^{(12)}) = 0, \tag{A.7}$$

$$\begin{aligned}
&\sum_{i=1}^{M_j^{(12)}} \Bigg\{ \nu_{ij}^{(12)}\mu_{ij}^{(12)} e^{\frac{1}{2}(\phi_{ij}^{(12)}(\nu_{ij}^{(12)}))^2}(Q_{ij}^{(12)} - \nu_{ij}^{(12)}) \cdot \\
&\left(\int_0^{Q_{ij}^{(12)}} \phi_{ij}^{(12)}(D)\frac{e^{-\frac{1}{2}(\phi_{ij}^{(12)}(D))^2}}{\sqrt{2}} dD + 2e^{-(\phi_{ij}^{(12)}(Q_{ij}^{(12)}))^2}\phi_{ij}^{(12)}(Q_{ij}^{(12)})\right)\Bigg\} = 0, \forall j \in \{1,\ldots,N\},
\end{aligned} \tag{A.8}$$

and

$$\sum_{i=1}^{M_j^{(13)}} \left\{ \nu_{ij}^{(13)} \mu_{ij}^{(13)} e^{\frac{1}{2}(\phi_{ij}^{(13)}(\nu_{ij}^{(13)}))^2} (Q_{ij}^{(13)} - \nu_{ij}^{(13)}) \cdot \left(\int_0^{Q_{ij}^{(13)}} \phi_{ij}^{(13)}(D) \frac{e^{-\frac{1}{2}(\phi_{ij}^{(13)}(D))^2}}{\sqrt{2}} dD + 2e^{-(\phi_{ij}^{(13)}(Q_{ij}^{(13)}))^2} \phi_{ij}^{(13)}(Q_{ij}^{(13)}) \right) \right\} = 0, \forall j \in \{1, \ldots, N\}. \tag{A.9}$$

Note that, given the variation among the contract quantities and prices (Q_{ij} and p_{ij}) of the 7098 total SKU's in our estimation (as demonstrated in Table A.2 below), none of the $2N+2$ equations in (A.6)-(A.9) can structurally be written as a perfect algebraic combination of a subset of the others. Therefore, for any solution to (A.6)-(A.9) in our estimation, r_{cl}, c_g, $\{\xi_j^{(12)}\}$ and $\{\xi_j^{(13)}\}$ are identifiable.

Table A.2: Statistics of Quantity and Retail Price Observations

	2012				2013				
	Order Quantity		Price		Order Quantity		Price		
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Total Sample Size
Auto parts	1819.54	10797.13	133.91	299.92	3635.60	14593.92	130.15	309.88	1128
Baby and Pregnancy products	3517.31	6297.05	75.77	72.84	4512.83	9152.56	74.35	72.16	546
Ceramics	775.29	1540.66	135.06	131.39	1327.28	1964.16	106.30	115.75	14
Clothing	1182.52	9498.33	1062.83	1274.77	1099.60	6150.71	1018.63	1247.93	548
Coffee	525.05	889.35	164.23	161.12	450.75	682.19	146.09	147.93	88
Computer accessories	6538.74	29266.85	219.49	273.25	9731.64	35528.31	182.26	233.09	296
Cosmetics	4904.61	14605.00	177.55	199.59	7632.79	19551.02	171.49	209.90	538
Electronic products	5470.08	27639.64	320.88	874.84	8573.63	45494.09	293.90	800.83	1926
Home improvement	539.65	1145.82	294.28	205.51	2162.78	4512.52	268.48	199.98	128
Household appliances	1896.67	6554.77	619.64	1450.03	3275.87	10421.53	549.76	1340.72	423
Sporting goods	646.01	2750.00	438.40	1364.72	683.73	2382.54	414.08	1335.89	552
Staple goods	4586.76	9583.81	158.20	242.29	8237.40	20549.81	151.91	223.14	741
Wine	1080.20	2395.17	334.47	704.20	4062.91	7885.89	289.27	468.91	164

Proof of Proposition 5: We start by plugging in the interest rate constraint in (3.5) to the objective function. The objective function in (3.5) becomes:

$$\max_{Q,l\geq 0}\Pi_r(Q,w,l) = \max_{Q,l\geq 0}\{\mathbb{E}[p\min\{Q,D\} + w\left(\tfrac{wQ-B}{w} - \min\{Q,D\}\right)^+ + (B_0 - wQ)(1+r_f)]\}\,. \tag{A.10}$$

From (A.10), we have $\frac{d\Pi_r(Q,l)}{dl} = 0$, implying that retailer will be indifferent about the amount l to borrow so long as the budget constraint is satisfied. However, to avoid trivial solutions in which retailer borrows more than needed and reinvest the extra amount borrowed in bank, we will assume that the retailer will borrow the exact amount to cover his purchase, we also assume that $B_0 > 0$. Thus, given a wholesale price w, the optimal order quantity can be found by setting the first order derivative to 0, i.e. $d\Pi_r(Q,l)/dQ = 0$. Doing so gives:

$$p(1-F(Q)) + wF\left(Q - \frac{B_0}{w}\right) - w(1+r_f) = 0\,. \tag{A.11}$$

As $Var[D] \to 0$, $F\left(Q - \frac{B_0}{w}\right) = 0$ for any $B_0 > 0$, and $d\Pi_r(Q,l)/dQ = p(1-F(Q)) - w(1+r_f)$. Thus, given the wholesale price w, the retailer's best response is to order

$$Q^*(w) = F^{-1}\left(1 - \frac{w(1+r_f)}{p}\right)\,. \tag{A.12}$$

We then proceed to check if the second order condition holds. Since

$$\frac{d^2\Pi_r(Q,l)}{dQ^2} = -pf(Q) < 0 \tag{A.13}$$

we have that when $Var[D] \to 0$, $d^2\Pi_r(Q,l)/dQ^2 < 0$ and π_r is concave in Q.

Now, knowing (A.11), which shows retailer's best response $Q^*_{lf}(w)$ to a given wholesale price, supplier sets the wholesale price w^*_{lf} such that his own profit is maximized, i.e. $d\Pi_s(Q^*(w), w)/dw = 0$. We substitute $\Pi_s(Q^*(w), w)$ by the supplier's objective function and we have:

$$\begin{aligned} &Q^*_{lf}(w)(1+r_f) + (w-c)\tfrac{dQ^*_{lf}(w)}{dw}(1+r_f) + \textstyle\int_0^{Q^*_{lf}(w)-\frac{B_0}{w}} Df(D)dD \\ &-(Q^*_{lf}(w) + w\tfrac{dQ^*_{lf}(w)}{dw})F(Q^*_{lf}(w) - \tfrac{B}{w}) = 0, \end{aligned} \tag{A.14}$$

Note that when $Var[D] \to 0$, $f(Q - B_0/w) = 0$ for $B_0 > 0$. Thus, $d\Pi_s(Q(w), w)/dw$ can be written as

$$\frac{d\Pi_s(Q^*(w), w)}{dw} = Q^*_{lf}(w)(1+r_f) + (w-c)\frac{dQ^*_{lf}(w)}{dw}(1+r_f)\,, \tag{A.15}$$

and the second derivative can be written as

$$\frac{d^2\Pi_s(Q^*(w), w)}{dw^2} = 2\frac{dQ^*_{lf}(w)}{dw}(1+r_f) + (w-c_p)\frac{d^2Q^*_{lf}(w)}{dw^2}\,. \tag{A.16}$$

According to implicit function theorem, it's known that

$$\left.\frac{dQ(w)}{dw}\right|_{Q(w)=Q^*_{lf}(w)} = -\frac{\partial G(Q,w)/\partial w}{\partial G(Q,w)/\partial Q} \overset{\sigma\to 0}{=} -\frac{1+r_f}{pf(Q)}\,, \tag{A.17}$$

and that

$$\left.\frac{d^2Q(w)}{dw^2}\right|_{Q(w)=Q^*_{lf}(w)} = -\frac{(1+r_f)}{p}\frac{dQ^*_{lf}(w)}{dw}\frac{f(Q^*_{lf}(w))}{f'(Q^*_{lf}(w))} = \frac{(1+r_f)^2}{p^2 f(Q^*_{lf}(w))}\frac{d}{dw}\left.\left(\frac{1}{f(Q(w))}\right)\right|_{Q(w)=Q^*_{lf}(w)} \tag{A.18}$$

When w is smaller than $p/(1+r_f)$, $Q^*_{lf}(w) = F^{-1}(1-w(1+r_f)/p) \to \mathbb{E}[D]$, and $f(Q^*_{lf}(w)) \to \infty$. As a result, when $w < p/(1+r_f)$

$$\frac{d\Pi_s(Q^*(w),w)}{dw} = \mathbb{E}[D](1+r_f) > 0\,. \tag{A.19}$$

When $w \to p/(1+r_f)$, $Q^*_{lf}(w) \to 0$. Thus

$$\frac{d\Pi_s(Q^*(w),w)}{dw} = -\frac{1+r_f}{pf(0)} < 0\,. \tag{A.20}$$

Thus, $dQ(w)/dw = 0$ occurs when $w \to p/(1+r_f)$, which indicates that $w^* \to p/(1+r_f)$ and $Q^*_{lf} \to 0$. As a result, $\Pi_s(Q^*(w),w)$ is concave in w since

$$\frac{d}{dw}\left.\left(\frac{1}{f(Q(w))}\right)\right|_{Q(w)=0} < 0 \tag{A.21}$$

is satisfied.

The proofs for FIFO and full buy back proceed in a similar way and is thus omitted here. ■

A.4 Derivations of the Distribution Parameter Updates in Demand Estimation

For ease of exposition, we derive the results using the whole sample as a whole instead of decomposing the whole sample by car model. Let n be the total sample size, and, without loss of generality, let the first m observations on sales are not binding, while the rest $n-m$ entries bind. In addition, denote D_i and $D_{i(obs)}$ to be the real demand and observed demand, respectively. Thus, the likelihood function can be written as:

$$\begin{aligned}\mathcal{L}(\beta;\beta',D_i) = -\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2}\sum_{i=1}^{m}\frac{(\log(D_i)-\boldsymbol{Z_i}^T\beta_{EM})^2}{\sigma^2} \\ -\frac{1}{2}\sum_{i=m+1}^{n}\frac{(\mathbb{E}[\log(D_i)|\beta',D_{obs(i)}]-\boldsymbol{Z_i}^T\beta_{EM})^2}{\sigma^2}.\end{aligned} \tag{A.22}$$

As shown in Tunca and Zhu [58], the likelihood function is concave in β_{EM}. Thus, taking derivative of the likelihood function stated above with respect to each parameter, β_{EM}^1, β_{EM}^2 and etc., we obtain the following set of equations:

$$\begin{pmatrix} n & \sum_1^n \log(w_i) & \sum_1^n I_{\{M=1\}} & \dots & I_{\{Q=4\}} \\ \sum_1^n \log(w_i) & \sum_1^n (\log(w_i))^2 & \sum_1^n \log(w_i) I_{\{M=1\}} & \dots & \sum_1^n \log(w_i) I_{\{Q=4\}} \\ \sum_1^n I_{\{M=1\}} & \sum_1^n \log(w_i) I_{\{M=1\}} & \sum_1^n I_{\{M=1\}} & \dots & \sum_1^n I_{\{M=1\}} I_{\{Q=4\}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum_1^n I_{\{Q=4\}} & \sum_1^n \log(w_i) I_{\{Q=4\}} & \sum_1^n I_{\{M=1\}} I_{\{Q=4\}} & \dots & \sum_1^n I_{\{Q=4\}} \end{pmatrix} \begin{pmatrix} \beta_{EM}^1 \\ \beta_{EM}^2 \\ \beta_{EM}^3 \\ \vdots \\ \beta_{EM}^{13} \end{pmatrix}$$

$$= \begin{pmatrix} \sum_1^m \log(D_i) + \sum_{m+1}^n \mathbb{E}[\log(D_{ij}) | \beta'_{EM}, D_{obs(i)}] \\ \sum_1^m \log(D_i) \log(w_i) + \sum_{m+1}^n \mathbb{E}[\log(D_{ij}) | \beta'_{EM}, D_{obs(i)}] \log(w_i) \\ \sum_1^m \log(D_i) I_{\{M=1\}} + \sum_{m+1}^n \mathbb{E}[\log(D_{ij}) | \beta'_{EM}, D_{obs(i)}] I_{\{M=1\}} \\ \vdots \\ \sum_1^m \log(D_i) I_{\{Q=4\}} + \sum_{m+1}^n \mathbb{E}[\log(D_{ij}) | \beta'_{EM}, D_{obs(i)}] I_{\{Q=4\}}\,, \end{pmatrix} \tag{A.23}$$

which can be summarized as $\boldsymbol{T}'\beta_{EM} = y$. Since the dummies for car model, quarter, car body type and city tier are not perfectly correlated to each other, $\boldsymbol{T}$ has full rank and is invertible. Thus, given that the EM algorithm is proved to converge, by iteratively calculating

$$\beta_{EM} = \boldsymbol{T}'^{-1} y\,, \tag{A.24}$$

we are able to obtain the values for β_{EM}^* under uncensored demand. ■

■

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