Management Science

Publication details, including instructions for authors and subscription information:
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https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–19
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Managing Channel Profits with Positive Demand Externalities

Long Gao,[a] Dawei Jian,[b,*] Mehmet Gumus,[c] Birendra K. Mishra[a]

[a] School of Business, University of California, Riverside, California 92521; [b] Sheldon B. Lubar College of Business, University of Wisconsin-Milwaukee, Milwaukee, Wisconsin 53202; [c] Desautels Faculty of Management, McGill University, Montreal, Quebec H3A 1G5, Canada

*Corresponding author

Contact: long.gao@ucr.edu, https://orcid.org/0000-0002-4417-2168 (LG); jiand@uwm.edu, https://orcid.org/0009-0005-2579-645X (DJ); mehmet.gumus@mcgill.ca, https://orcid.org/0000-0003-3814-896X (MG); barry.mishra@ucr.edu (BKM)

Received: January 2, 2021
Revised: March 28, 2022; August 17, 2023; December 15, 2023
Accepted: January 2, 2024
Published Online in Articles in Advance: January 31, 2025

https://doi.org/10.1287/mnsc.2021.00008

Abstract. Demand externalities arise when past sales stimulate future demand. They pervade many consumer markets. To penetrate such markets, how should manufacturers contract with retailers? We formulate the problem as a dynamic game, wherein the retailer can privately observe and control evolving market conditions, and consumers can act either myopically or strategically. Our contribution is threefold. (i) We characterize the optimal contract: It resolves a dynamic tradeoff between exploiting demand externalities, screening new information, and optimizing channel efficiency; moreover, it has a simple implementation of quantity discount. (ii) We characterize the dual role of demand externalities. Although demand externalities can improve channel surplus by expanding market size, they can also exacerbate information friction by enhancing the retailer's ability to manipulate the market. Ignoring the dark side of the agency cost, previous studies may have overestimated the benefit of demand externalities. (iii) We provide new practical guidance. We show private information per se need not hurt channel efficiency: The manufacturer can use recursive advance selling to extract new information for free. Our results also shed light on when and why manufacturers should moderate demand externalities and prefer long-term contracts. By highlighting the dual role of demand externalities in long-run channel performance, this study sharpens our understanding of channel theory and practice.

History: Accepted by Dmitri Kuksov, marketing.
Funding: L. Gao was partly supported by Academic Senate COR Grants of UCR.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/mnsc.2021.00008.

Keywords: distribution channel • diffusion • word-of-mouth • social learning • information asymmetry • advance selling

1. Introduction

Demand externalities arise when past sales stimulate future demand (Xie and Sirbu 1995). As consumers' choice interdependence, they pervade many retail markets; for example, video games (Dubé et al. 2010, Prieger and Hu 2012, Chao and Derdenger 2013, Lee 2013, Derdenger 2014), game consoles (Nair 2007, Liu 2010), Personal Digital Assistants (Nair et al. 2004), PC products and services (Tellis et al. 2009), digital TVs (Gupta et al. 1999, Bhaskaran and Gilbert 2005), network services (Katona et al. 2011), razors and blades (Hartmann and Nair 2010), smartphones (Liu and Luo 2023), movies, books, and e-readers (Liu 2006, Moretti 2011, Li 2019). In all these cases, early buyers influence later ones through either social learning or network effects (Godes et al. 2005, Hartmann et al. 2008, Peres et al. 2010).[1] For example, later buyers may benefit from the experience of early buyers through word-of-mouth communication and product reviews; they may also benefit directly from early buyers through increased social value of the installed base and service networks (Tucker 2008).

In such markets, retailers not only hold superior knowledge of evolving market conditions but can also influence the diffusion dynamics (Nair 2019). Besides pricing, they can manipulate the shopping environment, for example, by controlling how easily the consumers can compare products, how much product information to display, whether to post customer reviews or its own reviews, and whether to offer personalized recommendations (Mayzlin 2016). To sell products through such retail channels, how should manufacturers design contracts?

The problem is challenging for two reasons. The first is the agency problem. In a distribution channel, the two parties are strategic players pursuing divergent interests. Their relationship is often strained by information asymmetry: The retailer enjoys an information advantage over the manufacturer due to his expertise and control of consumer market conditions (Gao and Mishra 2019). The information is critical for a wide range of channel decisions. Yet without proper incentives, the retailer is unwilling to forgo his information advantage:

Although he can share the information to improve channel efficiency, he can also abuse it to extract *information rent*. As such, the agency problem arises and the channel efficiency suffers (Arya and Mittendorf 2004).

The second challenge is *demand externalities*.[2] Despite the potential for market growth, demand externalities can inflict contractual headaches. First, demand externalities systematically change the retailer's market condition and preference over time: The larger the retail market size, the better contract terms the retailer can demand. In response, the manufacturer may have to adjust the price and quantity based on new information, taking into account how her adjustment affects future retailer behavior. Second, demand externalities endogenize information asymmetry, producing a sequence of private information. In each period, the retailer can gain new market information, control its evolution through sales, and enhance his bargaining position. In response, the manufacturer may have to screen information sequentially, pay higher information rent, and intensify sales distortion. These requirements impose sequential incentive constraints, involving dynamic private information that arises endogenously over time. A nontrivial task for contract design.

This class of contracting problems are common in practice. Take the relationship between Xiaomi and Flipkart as an example. Xiaomi is a Chinese smartphone manufacturer. To penetrate the Indian market, it signs exclusive contracts with Flipkart. As an Indian domestic retailer, Flipkart has two advantages over Xiaomi. First, Flipkart has an information advantage, due to its local expertise, heavy investment in big data, and superior knowledge of Indian consumer preferences.[3] Second, Flipkart can shape the product sales and diffusion process, for example, through its online review systems, recommendation systems, and extensive networks on WhatsApp (Bapna 2012, Sridhar 2014, Dean 2023).[4] These communication channels allow Flipkart to exploit demand externalities for market growth: Through word-of-mouth, consumers can share experience and exchange product information, thereby reducing search cost and quality risk; through network effects, consumers can forge new friendships and gain a sense of belonging to a large community, thereby deriving enhanced utilities.[5] In such situations, how should Xiaomi contract with Flipkart?

The channel literature is largely silent on how to write such a contract. The extant literature has mainly focused on static settings with exogenous information asymmetry. As such, it offers limited guidance on how to sell products over time through distribution channels with demand externalities. In this paper, we study how demand externalities drive channel contacting and long-run performance. We address three questions. (i) What is the optimal contract? (ii) How do demand externalities change the existing insights? (iii) What are the implications for channel management?

We formulate the problem as a dynamic game. In our model, consumers can either buy immediately or delay purchase strategically, based on both intrinsic valuation and social influence; the retailer (he) can privately observe and control the evolving market conditions; and the manufacturer (she) designs a contract that governs the channel for multiple periods. In each period, the retailer learns new market information, orders the product, sets the retail price, and collects sales revenue; the manufacturer produces the retailer's order, and updates her market forecast (belief). Both firms are forward-looking and profit-maximizing.

The main conceptual challenge is how to *price* the retailer's information advantage. The retailer can privately observe and control market diffusion; exploiting this advantage, he can misreport for higher profit. To dissuade him, the manufacturer must pay the potential gain the retailer expects from all the misreporting opportunities. We first show that each act of selling has both carryover and externality effects, which measure how current market conditions and sales affect future market conditions. Then we pinpoint the information rent as the sum of the weighted misreporting gains over time, where the weight is the carryover effect, adjusted for demand externalities. Hence, the information rent—the price for truthful information sharing—is precisely the option value of all the misreporting opportunities during the entire relationship.

We find the optimal contract differs substantially from conventional ones in structure and performance. It resolves a dynamic tradeoff between exploiting demand externalities, screening new information, and optimizing channel efficiency. (i) To exploit demand externalities, the manufacturer should set aggressive sales and payment schedules. The purpose is to motivate the retailer to sell more and stimulate market growth. (ii) To screen new information, the manufacturer should offer advance selling recursively: She should charge expected future rent in the current period and refund it later contingent on future market conditions. This recursive mechanism ensures that the retailer has a stake in future channel efficiency, thereby committing him to sharing information truthfully over time. (iii) To optimize channel efficiency, the manufacturer should price discriminate across type and over time: She should sell and pay more for a retailer with better market conditions, and she should adjust production dynamically based on new information. The payment differential ensures that the retailer is willing to sell to the best of his market potential. The dynamic adjustment helps the manufacturer to tailor production to actual market size, thereby adapting to changing market conditions (He et al. 2008).

We find that the optimal contract unifies the classical first- and second-best policies: in the short run, it resembles the second best, because the information friction is still severe; in the long run, it converges to the first best, because information friction vanishes but demand externalities persist. The pace of convergence depends on the rate of market carryover across time. The long-run performance is mainly driven by market carryover and demand externalities: The prior type distribution—the main driver of the classical second best—plays no role in the long run.

We characterize the dual role of demand externalities. The first is the well-known *efficiency role*: By increasing market size, demand externalities can improve channel surplus. The second is the novel *agency role*: By enhancing the retailer's ability to manipulate future markets, demand externalities can either alleviate or aggravate information friction (asymmetry). As such, demand externalities induce *counterveiling incentives*. Depending on how they shape market diffusion, the manufacturer may either leverage externalities by promoting sales, or limit demand externalities by restricting sales. The sales restriction tends to occur in the early stage of the relationship, when information friction is still severe. As such, demand externalities can *reduce* channel efficiency—a stark contrast to the conventional view.

Our results have practical implications. We identify when and why firms should prefer long-term contracts and offer recursive advance selling. More importantly, we quantify when and why our contract can improve the classical second best. (i) Without a long-term perspective, the second-best orders too little, traps the channel in a low-efficiency equilibrium, and hence wastes the potential of demand externalities; (ii) because it is renewed every period, the second-best contract allows the retailer to retain real information advantage over time. This deficiency prolongs output distortion and rent payment, thereby perpetuating inefficiency. By contrast, our contract can mitigate both growth and information deficiencies. Hence, it can outperform the second best in a wide range of situations. The improvements are substantial, especially in durable relationships with strong demand externalities. In these circumstances, our contract should prevail.

2. Literature Review

We study a new class of channel problems—how product diffusion affects optimal contract design. The diffusion literature is vast (Mahajan et al. 1990, Nair 2019). A central question is how social interactions drive consumer choice and firm profit (Peres et al. 2010). A main finding is that demand externalities arise when past sales stimulate future demand (Xie and Sirbu 1995). Demand externalizes have two underlying drivers. (i) The first is *social learning*: Through word-of-mouth communication, later buyers can learn from the experience of early buyers (Bass 1969). Therefore, social learning creates *information externalities*, which benefit later buyers by reducing their search cost and quality risk.[6] (ii) The second driver is *network effects*. They arise when the buyer's utility of a product increases as more consumers buy the same product (Tucker 2008). Therefore, network effects generate *payoff externalities*, which benefit later buyers by increasing the social value of the product. Network effects are direct, when the utility increases with the number of users of the same product, for example, fax, phone, and email (Farrell and Klemperer 2007). They are indirect, when the utility increases with the number of users of the complementary product; for example, DVD players and titles (Dubé et al. 2010).[7]

Demand externalities are central to the Bass diffusion framework. Bass (1969) finds that new sales are driven by both *external influence p* (e.g., prices and advertising), and *internal influence q* from consumers' social interactions (e.g., word-of-mouth communication). But the Bass model itself only describes the aggregate adoption behavior by a logistic curve (Riccati equation), without explicitly modeling underlying drivers of diffusion. An important trend of diffusion research is to explicate how various types of internal influences—such as network effects and social learning—create demand externalities (Goldenberg et al. 2010, Perakis and Roels 2010). In essence, demand externalities are the consumers' *choice* interdependence, the *consumption complementarity* that arises when past and expected future sales increase current demand (Hartmann et al. 2008, Hartmann 2010). To exploit demand externalities, firms can deploy a wide range of strategies; for example, seeding (Kempe et al. 2003), referral rewards (Lobel et al. 2017, Kamada and Öry 2020), viral product design (Aral and Walker 2011), sequential launch (Aoyagi 2010), hired "trendsetters" and influencers (Galeotti and Goyal 2009, Chatterjee and Dutta 2016), product quality and variety (Godes 2017, Kuksov and Liao 2019), consumer review (Chen and Xie 2008), and dynamic pricing (Xie and Sirbu 1995; Jing 2011a, b; Papanastasiou and Savva 2017).

We enrich the diffusion literature in two ways. First, this literature mainly focuses on business-to-consumer (B2C) settings. Despite the prevalence of business-to-business (B2B) transactions (Lilien 2016), optimal channel contracting for product diffusion remains an open question. Our study fills the void. We show once the retailer is in the game, the new strategic behaviors arise, and they can change the existing insights considerably. Second, this literature usually assumes complete information, revealing only the bright side of demand externalities. We reveal a dark side of demand externalities: Once information asymmetry is considered, demand externalities *can* exacerbate agency costs and hurt firms; the optimal output can go either above the classical first-best or below the second-best. Ignoring the dark side, previous studies may have overestimated the benefit of demand externalities.

Our work connects contract design with advance selling. Advance selling decouples purchase from consumption, allowing sellers to book sales long before consumption (Shugan and Xie 2000).[8] The literature provides several justifications for advance selling (Xie and Shugan 2009). For example, advance selling can segment the market for price discrimination (Dana 1998), hedge demand uncertainty (Subramanian et al. 1999a), divert excess demand off-peak times (Gale and Holmes 1993), mitigate capacity shortage (Desiraju and Shugan 1999), leverage buyer uncertainty (Xie and Shugan 2001), and profit from customer cancellations (Xie and Gerstner 2007). We offer a new justification—advance selling can also serve as a screening device to alleviate adverse selection.

Our work contributes to the channel literature on information asymmetry (Sudhir and Datta 2009).[9] This literature relies on the adverse selection and signaling paradigms. A central theme is how to reduce inefficiencies of information asymmetry.[10] For adverse selection problems, the literature has three general insights (Mussa and Rosen 1978): (i) the agent (retailer) should benefit from his private information; (ii) the principal should pay information rent and distort output (sales); and (iii) the first best is unattainable. These insights assume a static context with exogenously fixed private information. They rule out the possibility to control and respond to new information arising gradually over time—a fundamental function of the channels with demand externalities. By contrast, we show once demand externalities are considered, the three general insights may no longer hold. In particular, the first best is attainable when private information arrives independently over time. Hence, conventional insights are not robust to the assumption of fixed private information: Ignoring information endogeneity, previous studies may have overestimated the harm of information asymmetry.

To our knowledge, this study is the first attempt to design *optimal contracts* for goods with demand externalities and evolving market conditions. Using mechanism design, we build a *normative model* and provide guidance for *improving current channel practice*.[11] The results provide testable implications for future empirical inquiries. For example, we show the optimal contract may feature recursive advance selling. However, this feature is not widely used by practitioners.[12] Given our theoretical prediction, one may use field experiments to test how incorporating recursive advance selling can improve channel performance; see Misra and Nair (2011) for a similar endeavor.[13]

3. Model

We consider a channel contracting problem, where an upstream manufacturer (she) produces and sells a product through a downstream retailer (he). Both parties are strategic, forward-looking, and profit-maximizing, with a discount factor $\delta \in (0,1)$. To ensure business continuity, the manufacturer writes a long-term contract that governs the relationship for K periods. The retailer has superior knowledge of evolving market conditions $\theta_t \in \Theta \equiv [\underline{\theta}, \bar{\theta}]$, whereas the manufacturer knows only the prior distribution F of θ_1. All other parameters are common knowledge. Table 1 defines all the notation.

The dynamic game plays out as follows (Figure 1). (i) At the outset, the manufacturer offers the retailer a contract $\phi = (\phi_t)_{t=1}^K$, where the *payment schedule* $\phi_t : \mathbb{R}_+ \to \mathbb{R}$ specifies total payment $\hat{T}_t = \phi_t(\hat{q}_t)$ for supplying quantity $\hat{q}_t$ in period t. (ii) The retailer with private information θ_1 decides $a \in \{0,1\}$ whether to accept the contract: If he accepts, the game continues; otherwise, the game ends. (iii) In period t, upon observing θ_t, the retailer orders $\hat{q}_t$ and pays $\hat{T}_t = \phi_t(\hat{q}_t)$; then the manufacturer produces $\hat{q}_t$ at unit cost c. (iv) Upon receiving $\hat{q}_t$, the retailer charges retail price $\hat{p}_t$, makes sales $\hat{q}_t = \theta_t - \hat{p}_t$, and collects revenue $R_t = \hat{p}_t \cdot \hat{q}_t = (\theta_t - \hat{q}_t) \cdot \hat{q}_t$; the leftover stock has zero salvage value. (v) The market condition evolves to θ_{t+1} and the game advances to period $t+1$. To avoid triviality, we assume cost c is sufficiently small so that sales are positive.

3.1. Market Dynamics

At the aggregate level, market condition θ_t can evolve for three reasons. First, θ_t can persist because of the *carryover effect* (Dekimpe et al. 2008): $(\theta_t)_{t\geq 1}$ are often serially correlated, for example, due to consumers' habit persistence and forward-looking behavior. As such, similar market conditions tend to persist for a while before changing substantially to another one (Chintagunta et al. 2006). Second, θ_t can change due to *demand externalities*: The larger the past sales, the more attractive the product becomes, and the greater the future market size (Parakhonyak and Vikander 2019, Kamada and Öry 2020). Third, θ_t can fluctuate, due to *random shocks*, such as consumer preference shift, competitive moves, and business cycles (Villas-Boas 1999).

We model the market diffusion $\theta_{t+1} = Z(\theta_t, q_t, \varepsilon_{t+1})$ by

$$\theta_{t+1} = \alpha\theta_t + \beta q_t + \varepsilon_{t+1}, \quad (1)$$

where $\alpha \in [0,1)$ is the market carryover rate, $\beta \geq 0$ is the market growth rate, and $\varepsilon_{t+1} \sim G$ is the random shock. Given (θ_t, q_t), the future market condition θ_{t+1} follows conditional distribution $F(\theta_{t+1}|\theta_t, q_t) = G(\theta_{t+1} - \alpha\theta_t - \beta q_t)$. Hence, $(\theta_t)_{t\geq 1}$ are a diffusion process controlled by sales policy $(q_t)_{t\geq 1}$: they are *outcomes* of the retailer-consumer interactions in the end market.

Our model has two salient features. The first is *dynamic learning*: each period the retailer can learn new information ε_{t+1} and improve forecasting θ_{t+1} over time; through interactions, the manufacturer can also elicit the new information and update her belief accordingly. The second feature is *endogeneous information asymmetry*. Because of his expertise and close contact with

Table 1. Notation

Symbol	Description
$\equiv$	Equal by definition
α	Market carryover rate, $\alpha \in [0,1)$
β	Market growth rate, $\beta \in [0,\infty)$
δ	Discount factor, $\delta \in (0,1)$
θ_t	Retailer's market condition in period t, $\theta_t \in \Theta = [\underline{\theta}, \bar{\theta}] \subset \mathbb{R}$
θ^t	History of market conditions till time t, $\theta^t \equiv (\theta_1, \theta_2, \ldots, \theta_t) = (\theta_s)_{1\le s\le t}$
$\hat{\theta}^t$	Reports of market conditions till time t, $\hat{\theta}^t \equiv (\hat{\theta}_1, \hat{\theta}_2, \ldots, \hat{\theta}_t)$
$\mathcal{P}$	Contracting environment
ϕ	Contract, with quantity q_t and payment T_t for period t, $\phi = (q_t, T_t)_{t=1}^K$
K	Contract duration
E_t^ϕ	Expectation given contract ϕ and the information available at time t
F	CDF of θ_1, with density f
$F(\cdot\|\theta_{t-1}, q_{t-1})$	Conditional distribution of θ_t, with conditional density $f(\cdot\|\theta_{t-1}, q_{t-1})$
$f^t(\theta_{t+1}\|\theta_1)$	t-step conditional density function of θ_{t+1} given θ_1
ε_t	Market shock in period t, $\mathsf{E}\varepsilon_t = \mu$
G	Distribution of shock ε_t
$h(\theta)$	Inverse hazard rate of F, $h(\theta_1) = \frac{1-F(\theta_1)}{f(\theta_1)}$
c	Manufacturer's unit production cost
$R(\theta_t, q_t)$	Retailer's revenue function in period t
$J_t(\theta^t)$	Manufacturer's continuation profit from period t onward
$U_t(\theta^t)$	Retailer's continuation profit from period t onward
$\pi_t(\theta_t, q_t)$	Flow channel surplus in period t, $\pi_t(\theta_t, q_t) \equiv R(\theta_t, q_t) - cq_t$
$\Pi_t(\theta^t)$	Continuation channel surplus from period t onward, $\Pi_t(\theta^t) \equiv \mathsf{E}[\sum_{\tau\ge t}\delta^{\tau-t}\pi_\tau(\theta_\tau, q_\tau)\|\theta^t]$
$\lambda_t(\theta_t)$	Marginal surplus gain from demand externalities, $\lambda_t(\theta_t) \equiv \frac{\partial}{\partial q_t}\mathsf{E}[\Pi_{t+1}\|\theta_t]$
$\rho_t(\theta_t)$	Marginal information cost from period t onward, $\rho_t(\theta^t) \equiv \frac{\partial}{\partial q_t}\mathsf{E}[\sum_{\tau\ge t+1}\delta^{\tau-t}h(\theta_1)\alpha^{\tau-1}q_\tau(\theta^\tau)\|\theta^t]$

consumers, the retailer is better informed about initial θ_1; after each sales q_t, he can also observe new information ε_{t+1}. He can manipulate his information advantage in two ways: By under-reporting θ_t, he can project a grim future θ_{t+1} and secure a better price from the manufacturer; by manipulating sales q_t, he can influence the future market and hence payoff. It turns out, these two manipulations are key to contract design.

3.2. Contract Design

By the *revelation principle*, we can focus on direct, truth-telling contracts (Myerson 1986). Because self-selection reveals preferences, *ordering* $\hat{q}_t$ is equivalent to *reporting* $\hat{\theta}^t \equiv (\hat{\theta}_1, \hat{\theta}_2, \ldots, \hat{\theta}_t)$: They both produce the same outcome ($\hat{q}_t = q_t(\hat{\theta}^t), \hat{T}_t = T_t(\hat{\theta}^t)$). We call the retailer who has time t history $\theta^t = (\theta_1, \ldots, \theta_t)$ the *retailer* θ^t. The long-term contract $\phi = (q_t, T_t)_{t=1}^K$ then reduces to a sequence of quantity-payment rules (functions), $q_t, T_t : \Theta^t \to \mathbb{R}_+$.

Given contract ϕ, the retailer finds his best response $(\hat{q}_t, \hat{T}_t)_{t=1}^K$ by solving a dynamic program: Retailer θ^t self-selects quantity $q_t(\hat{\theta}^t)$ from ϕ (or reports $\hat{\theta}^t$) to maximize his continuation payoff:

$$\tilde{U}_t(\hat{\theta}^t; \theta^t) = R(\theta_t, q_t(\hat{\theta}^t)) - T_t(\hat{\theta}^t) + \delta\mathsf{E}[U_{t+1}(\hat{\theta}^t, \theta_{t+1})|\theta_t, q_t(\hat{\theta}^t)],$$

where $R(\theta_t, q_t) \equiv (\theta_t - q_t)\cdot q_t$ is the *revenue function* and $U_{t+1}(\theta^{t+1}) \equiv \tilde{U}_{t+1}(\theta^{t+1}; \theta^{t+1})$ is his equilibrium payoff under the *truth-telling strategy* ($\hat{\theta}^t = \theta^t$, $\forall t$).

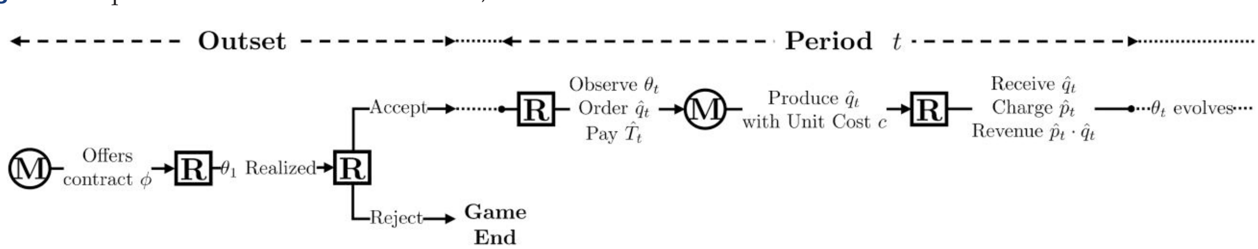
Anticipating the retailer's best response, the manufacturer designs contract ϕ to maximize her payoff:

$$\max_{\phi\in\Phi} \tilde{J}(\phi) = \mathsf{E}\left[\sum\nolimits_{t\ge 1}\delta^{t-1}(T_t(\theta^t) - c\cdot q_t(\theta^t))\right] \qquad (\mathcal{P})$$

$$\text{s.t. } U_1(\theta_1) \ge 0, \quad \forall\theta_1, \qquad (IR)$$

$$U_t(\theta^t) = \max_{\hat{\theta}^t} \tilde{U}_t(\hat{\theta}^t; \theta^t), \quad \forall\theta^t, \qquad (IC_t)$$

Figure 1. Sequence of Events: **M** = Manufacturer, **R** = Retailer



where $\Phi \equiv \{\phi : IR, IC_t, \ \forall t\}$ is the set of feasible contracts. Intuitively, the manufacturer designs ϕ to induce the *truth-telling* equilibrium play from retailer θ^t: He will participate (IR) and *self-select* the quantity $q_t(\theta^t)$ intended for him (IC_t), *as if* he were truthfully reporting her private information θ^t.

3.3. Key Modeling and Expositional Choices

We focus on the channel contracting problem under demand externalities. In our setting, demand externalities come from consumer social interactions: They can arise from either network effects or social learning, and consumers can be either myopic or strategic. The resulting model is a complex dynamic game with incomplete information, which is intractable in general (Nair 2019, p. 379). For the purpose of contracting, however, it is sufficient to consider revenue function $R(\theta_t, q_t)$ and aggregate market dynamics $\theta_{t+1} = Z(\theta_t, q_t, \varepsilon_{t+1})$—the *outcomes* of the retailer-consumer interactions. As such, we can directly model the contracting problem as one of mechanism design, taking functions R and Z as model primitives. For completeness, we detail the equivalent game-theoretic formulation in Online Appendix A.

We assume consumers can be either myopic or strategic. In particular, myopic consumers with network effects produce linear diffusion dynamics, whereas strategic consumers with social learning produce nonlinear dynamics. When consumers are strategic, they can either buy immediately or delay the purchase; hence, consumer choice depends on both past sales and *rational expectations* of the future. The central notion is the option value of strategic delay (Dixit and Pindyck 1994). Moreover, rational expectations are self-reinforcing: They generate feedback loops, where high expected future sales make buying more attractive, thereby increasing current sales. In our setting, given contract ϕ, the retailer's revenue function $R(\theta_t, q_t)$ and diffusion dynamics $\theta_{t+1} = Z(\theta_t, q_t, \varepsilon_{t+1})$ are the *outcomes* of the retailer-consumer interactions in the retail market. We detail the microfoundations for functions R and Z in Online Appendices B–D.

We assume the manufacturer can commit to a contract. This is a common practice in B2B transactions (Lilien and Grewal 2012). A modern distribution channel is capital intensive, requiring substantial sunk investment in manufacturing, logistics, and selling facilities (Cachon and Terwiesch 2008). Its success hinges on a stable flow of the product so that each member can operate their facilities efficiently. As a result, the manufacturer benefits from contractual commitments, especially in situations where renegotiation can invite opportunistic reactions and hurt reputation. Without commitment, the manufacturer may suffer from *ratchet effect*: The retailer is unwilling to share the information that could hurt his future self (Roberts and Milgrom 1992). Moreover, the contracts can be enforced through court systems, reputation mechanisms, and technologies such as smart contracts (Gulker 2017).[14] For these reasons, the majority of contracting papers assume commitment.[15]

Importantly, *contracting with commitment allows future revisions of actual trading terms.* It need not fix all terms once for all. Instead, it may simply set the *rules* for future transactions at the outset, as a menu of contingencies. Which contingency to execute, however, depends on the prevailing market condition in the future. In this sense, contracting with commitment does allow future revisions, within the rules specified at the outset. In our model, this flexibility is implemented through the state-contingent contract: Each term $(q_t(\theta^t), T_t(\theta^t))$ is not fixed numbers but rather the *functions* of prevailing market conditions. In the contracting literature, this is a standard way to incorporate contract revision (Bolton and Dewatripont 2005).

In what follows, we consider four regimes in sequel (Table 2), with increasing complexity in information structure and market dynamics. For transparency, our main model uses the two-period setup and linear dynamics; for completeness, we solve the general model with nonlinear dynamics in Section 7.

4. Full Information Benchmarks

In regime $\bar{\mathcal{P}}$, the manufacturer has *perfect* visibility and control: She can observe the retailer's market condition θ_t and dictate his sales q_t. Hence, she only needs to ensure retailer participation:

$$\bar{J}_1 = \max\{\tilde{J}(\phi) : \ IR\}. \qquad (\bar{\mathcal{P}})$$

The regime $\bar{\mathcal{P}}^n$ without demand externalities ($\beta = 0$) is a special case of $\bar{\mathcal{P}}$. To ensure (IR), it suffices to charge sales revenue $T_t = R(\theta_t, q_t)$. Let $\pi_t(\theta_t, q_t) \equiv R(\theta_t, q_t) - cq_t$ be the (flow) channel surplus in period t. Problem ($\bar{\mathcal{P}}$) then reduces to a centralized control that maximizes the net present value of channel surplus:

$$\bar{J}_1 = \max_{\phi} \Pi_1(\phi) \equiv \mathsf{E}^{\phi}[\pi_1(\theta_1, q_1) + \delta\pi_2(\theta_2, q_2)].$$

The key issue is how to exploit demand externalities, which requires extra initial sales to stimulate future demand. The main tradeoff is *intertemporal*, between current cost overrun and future gain from demand externalities. Let $\bar{\Pi}_1$ and $\bar{\Pi}_1^n$ be the optimal channel surplus in $\bar{\mathcal{P}}$ and $\bar{\mathcal{P}}^n$. Let $\lambda(\theta_1) \equiv \beta\mathsf{E}[\bar{q}_2(\theta_2)|\theta_1]$. We find the following.

Proposition 1. *Consider full information benchmarks,*

(a) *without demand externalities, the optimal contract $\bar{\phi}^n$ in $\bar{\mathcal{P}}^n$ is*

$$\bar{q}_t^n(\theta_t) = \frac{1}{2}(\theta_t - c), \qquad \bar{T}_t^n(\theta_t) = R(\theta_t, \bar{q}_t^n(\theta_t)), \quad \forall\theta_t, \ \forall t. \qquad (2)$$

Table 2. Four Regimes

	No demand externalities ($\beta = 0$)	Demand externalities ($\beta > 0$)
Full information	$\bar{\mathcal{P}}^n$	$\bar{\mathcal{P}}$
Asymmetric information	$\mathcal{P}^n$	$\mathcal{P}$

Note. We use bar $\bar{(\cdot)}$ to denote full information and superscript n to denote "no demand externalities."

(b) *with demand externalities, the optimal contract $\bar{\phi}$ in $\bar{\mathcal{P}}$ is*

$$\bar{q}_2(\theta_2) = \frac{1}{2}(\theta_2 - c),$$
$$\bar{q}_1(\theta_1) = \frac{(2+\delta\alpha\beta)\theta_1 - (2+\delta\beta)c + \delta\beta\mu}{4-\delta\beta^2},$$
$$\bar{T}_t(\theta^t) = R(\theta_t, \bar{q}_t(\theta_t)), \ \forall \theta_t, \ \forall t. \tag{3}$$

(c) *demand externalities increase channel surplus and initial sales:*

$$\bar{\Pi}_1 \geq \bar{\Pi}_1^n, \qquad \bar{q}_1(\theta_1) - \bar{q}_1^n(\theta_1) = \frac{\delta}{2}\lambda(\theta_1).$$

Part (a) is the classical first best (without demand externalities). In $\bar{\mathcal{P}}^n$, the retailer faces exogenous market conditions, $\theta_2 = \alpha\theta_1 + \varepsilon$. His initial sales q_1 have no bearing on the future. To control the retailer, the manufacturer solves a myopic optimization: The optimal quantity $\bar{q}_t^n$ equalizes the marginal revenue $\frac{\partial}{\partial q_t} R(\theta_t, q_t) = \theta_t - 2q_t$ with the marginal cost c. This is a demanding offer: It allows the manufacturer to perfectly match supply with demand, fully extract the *channel surplus* Π_1, and leave the retailer with zero profit (rent).

Part (b) is the first best with demand externalities. The key notion is the (marginal) surplus gain from demand externalities, $\lambda(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[\pi_2 | \theta_1]$. In $\bar{\mathcal{P}}$, the retailer has *endogenous* condition $\theta_2 = \alpha\theta_1 + \beta q_1 + \varepsilon$. His initial sales q_1 have both short- and long-term consequences: by selling $\mathrm{d}q_1$ more than the first-best $\bar{q}_1^n$, the channel will suffer short-term profit loss $[(\theta_1 - 2q_1) - c] \cdot \mathrm{d}q_1$, but it can also gain $\lambda(\theta_1) \cdot \mathrm{d}q_1$ from long-term demand externalities. The gain comes from expanding future market size (at rate β), enhancing future revenue ($R_\theta \equiv \frac{\partial}{\partial \theta_1} R = q_1 \geq 0$), and increasing future surplus ($\lambda(\theta_1) \geq 0$). The optimal contract $\bar{\phi}$ balances short-term loss with long-term gain, resulting in penetration pricing. Given perfect visibility, the manufacturer can still extract the entire surplus, and the retailer still has no ability to make profits.

Part (c) shows how to leverage demand externalities through initial sales. First, relative to the myopic first-best $\bar{q}_1^n$, the manufacturer in $\bar{\mathcal{P}}$ should sell more aggressively. The upward adjustment $(\bar{q}_1 - \bar{q}_1^n) = \frac{\delta}{2}\lambda$ is to *invest* in market growth; once the growth materializes, she can then *harvest* the increased market size θ_2 by expanding sales to $\bar{q}_2$. Second, the adjustment is driven by two factors: The greater the market carryover α, the higher the growth rate β, and the bigger the upward adjustment. When the market growth rate vanishes, so does the upward adjustment: $\bar{q}_1^n = \lim_{\beta \to 0} \bar{q}_1$.

The key takeaway is that demand externalities enhance surplus. By increasing future market size, demand externalities improve the value of the option to expand future sales for higher margin. The policy implications are immediate. Under full information, the manufacturer should raise output in early periods to internalize the option value of demand externalities; she should use *penetration pricing* with increasing price path; absent information friction, she can expropriate the entire gain from demand externalities.

These are classical results (Liu and Chintagunta 2009). They assume full information and simplistic behavior—Manufacturers are omniscient with perfect visibility. The assumption simplifies analysis by avoiding *strategic uncertainty*, but it also produces unrealistic predictions.[16] In practice, manufacturers only have limited visibility into retailers' market conditions and behavior. Such strategic uncertainty can fundamentally change equilibrium outcomes (Morris 1995). To make credible predictions, we must model information asymmetry and strategic behavior it entails.

5. Contracting Under Dynamic Information Asymmetry

With superior market information, the retailer can manipulate market information to secure a better price. The threat compels the manufacturer to pay information rent and distort sales. This is the classical solution for asymmetric information, which hurts channel efficiency (Arya and Mittendorf 2004). With demand externalities, the retailer can further enhance his ability to manipulate: Beyond initial θ_1, he can also observe new condition θ_2; by manipulating initial sales q_1, he can influence future market condition $\theta_2 \sim F(\cdot | \theta_1, q_1)$ and hence future profits.

In response, the manufacturer must entertain new solutions. First, she must ensure truth-telling in every period, because information asymmetry persists over time. Second, she must consider how initial sales affect future retailer behavior, because demand externalities endogenize information asymmetry. The key is how to set contingent sales targets, across type and over time. To better understand information friction and demand externalities, we examine two regimes $\mathcal{P}^n$ and $\mathcal{P}$ in sequel, with the usual assumption that the inverse hazard rate $h(\theta_1) \equiv \frac{1-F(\theta_1)}{f(\theta_1)}$ is nonincreasing.

5.1. Regime $\mathcal{P}^n$: Price for Sequential Information Sharing

When $\beta = 0$, market evolution is exogenous, and only information friction is at work. The retailer can privately observe multiple market signals: Before contracting, he observes θ_1; after initial sales q_1, he observes new information ε and infers $\theta_2 = \alpha\theta_1 + \varepsilon$. The manufacturer cannot observe θ_t, so she must screen it to better match supply with demand. Screening requires sequential constraints $(IC_t)_{t\geq 1}$ to guarantee truth-telling in all periods. The central issue is how to price the retailer's information advantage. The problem becomes

$$J_1^n = \max\{\tilde{J}(\phi): \ IR, \ IC_t, \ \forall t\}. \qquad (\mathcal{P}^n)$$

Proposition 2. *In regime $\mathcal{P}^n$, the optimal contract ϕ^n set quantity and payment as*

$$q_2^n(\theta^2) = \frac{1}{2}(\theta_2 - c) - \frac{1}{2}h(\theta_1)\alpha, \ T_2^n(\theta^2) = R(\theta_2, q_2^n(\theta^2)) - U_2^n(\theta^2),$$

$$q_1^n(\theta_1) = \frac{1}{2}(\theta_1 - c) - \frac{1}{2}h(\theta_1), \ T_1^n(\theta_1) = R(\theta_1, q_1^n(\theta_1)) - U_1^n(\theta_1) + \delta \mathsf{E}[U_2(\theta^2)|\theta_1],$$

where $U_1^n(\theta_1) = \int_{\underline{\theta}}^{\theta_1} \mathsf{E}[q_1^n(\tilde{\theta}_1) + \delta\alpha q_2^n(\tilde{\theta}_1, \theta_2)|\tilde{\theta}_1] \cdot \mathrm{d}\tilde{\theta}_1$ and $U_2^n(\theta^2) = \int_{\underline{\theta}}^{\theta_2} q_2^n(\theta_1, \tilde{\theta}_2) \cdot \mathrm{d}\tilde{\theta}_2$ are the profit (information rent) for retailer-θ_1 and θ^2.

The manufacturer offers contracts for two purposes: to screen information and to extract surplus. In the classic world $\mathcal{P}^c$, both firms are myopic ($\delta = 0$), and their interaction is one-shot; the optimal solution ϕ^c is to pay information rent and restrict sales. The solution allows the retailer θ_1 to profit $U_1(\theta_1)$ from the market advantage $R_\theta \, \mathrm{d}\tilde{\theta}_1 = q_1^n \, \mathrm{d}\tilde{\theta}_1$ he has over the low types: Instead of truth-telling, he has the *option* to underreport θ_1 and pocket in $q_1^n \, \mathrm{d}\tilde{\theta}_1$; to ensure truthful report, the manufacturer must pay the potential gain (rent) from the misreporting option, so that the retailer is indifferent between misreporting and truth-telling. The resulting rent $U_1(\theta_1) = \int_{\underline{\theta}}^{\theta_1} q_1^n \, \mathrm{d}\tilde{\theta}_1$ drives the payoff wedge (gap) between retailer θ_1 and $\underline{\theta}$. Moreover, restricting sales q_1^n for $\tilde{\theta}_1 < \theta_1$ can reduce rent payment $U_1(\theta_1)$. This is the central idea of the classical second-best ϕ^c (Mussa and Rosen 1978).

In regime $\mathcal{P}^n$, both parties are *forward-looking* ($\delta > 0$). Therefore, the classical solution is no longer sufficient. As fresh information θ_2 arises in period 2, the retailer gains new information advantages over the manufacturer. Because of market carryover ($\alpha > 0$), his advantage also spreads over time: Not only does he enjoy the market advantage today, but he tends to enjoy it tomorrow. To keep him honest, the manufacturer must discipline him sequentially: She must pay for the future advantages, in period 2 affected by initial θ_1. As such, the total rent $U_1(\theta_1)$ must *price in* all the misreporting opportunities, across type and over time. A challenging task.

The key is to compute the present value of market θ_1's carryover effect. Along the path (θ_1, θ_2), the initial condition θ_1 has the residual effect $\frac{\partial}{\partial\theta_1}\mathsf{E}[\theta_2|\theta_1] = \alpha$ over θ_2. This intertemporal linkage confers market advantage $q_2^n \, \mathrm{d}\tilde{\theta}_2$ in period 2, resulting in the revenue gain $\alpha \cdot q_2^n \, \mathrm{d}\tilde{\theta}_1$. Driven by initial θ_1, this is the requisite wedge for enforcing IC_2. Taking all such gains (wedges) over both periods into account, the manufacturer must "average" them over time and across type, paying retailer θ_1 the extra rent $\mathsf{E}[q_1^n + \delta\alpha q_2^n \,|\tilde{\theta}_1] \, \mathrm{d}\tilde{\theta}_1$. The extra rent is the sum of α-weighted revenues that retailer θ_1 can gain from misreporting over time. There are $[\underline{\theta}, \theta_1)$ such misreporting opportunities, so the manufacturer must pay retailer θ_1 the total rent

$$U_1(\theta_1) = \int_{\underline{\theta}}^{\theta_1} \mathsf{E}[q_1^n(\tilde{\theta}_1) + \delta\alpha q_2^n(\tilde{\theta}_1, \theta_2)|\tilde{\theta}_1] \cdot \mathrm{d}\tilde{\theta}_1. \qquad (4)$$

The rent payment is the *shadow price* for enforcing sequential truth-telling $(IC_t)_{t\geq 1}$: The greater the manufacturer's uncertainty (large $h(\theta_1)$), the greater the market advantage ($R_\theta = q_t^n$), the stronger the market carryover α, and the larger the rent payment. We can simplify the expected rent to

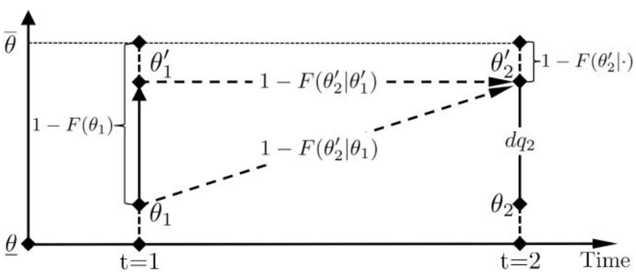
$$\begin{aligned} \mathsf{E}U_1(\theta_1) &= \mathsf{E}[(q_1^n(\theta_1) + \delta\alpha q_2^n(\theta_1, \theta_2)) \cdot h(\theta_1)] \\ &= \mathsf{E}[U_1'(\theta_1) \cdot h(\theta_1)]. \end{aligned} \qquad (5)$$

It is the expected product of marginal rent $U_1'(\theta_1)$ and hazard rate $h(\theta_1)$, depending on θ_1 only. This suggests that the rent is paid entirely for screening initial θ_1. As we shall show in Section 6, new information θ_2 can be extracted for free.

The rent structure (4) guides production planning. It suggests that the manufacturer can reduce rent $U_1(\theta_1)$ by restricting quantity $q_t^n(\theta_1', \theta_2)$ for lower type retailers $\theta_1' < \theta_1$. The restriction reduces the efficiency of low type retailer θ_1', but it helps reclaim the rents the manufacturer would otherwise concede to high type retailers. This is the key idea behind *quantity discount* (Moorthy 1987). What complicates production planning is the dynamic information structure: Unlike the static case, initial information θ_1 in $\mathcal{P}^n$ has long-term effects, spreading to period 2; moreover, the new information θ_2 arises over time. These dynamics allow retailer θ_1 multiple opportunities to misreport. To discipline him, the quantity restriction should also be dynamic: not only the initial quantity for retailers $\theta_1' < \theta_1$, but also their future quantity along path (θ_1', θ_2) should be properly restricted.

Using a perturbation argument, we can identify the optimal quantity $q_2^n(\theta^2)$ (Figure 2). In period 2, consider an infinitesimal increase $\mathrm{d}q_2$ at retailer θ^2. The perturbation ignites two countervailing effects. The first is the direct *surplus gain* $\frac{\partial}{\partial_{q_2}}\pi_2 \cdot \mathrm{d}q_2 = [(\theta_2 - 2q_2^n) - c] \cdot \mathrm{d}q_2$ at

Figure 2. Evolution of the Market Condition and Misreporting Incentives: $K = 2$



θ^2, which discounts back to the extra profit at θ_1:

$$\text{surplus gain} = \delta \cdot \underbrace{f(\theta_2|\theta_1) \cdot f(\theta_1)}_{\text{density } f(\theta^2)} \cdot [(\theta_2 - 2q_2^n) - c] \cdot \, \mathrm{d}q_2. \tag{6}$$

The second effect is the indirect *rent increase* due to sequential $(IC_t)_{t\geq 1}$. In period 2, as retailer θ^2 increases sales by $\mathrm{d}q_2$, IC_2 implies that his higher type peers (θ_1, θ_2') with condition $\theta_2' > \theta_2$ must each be paid an additional $\frac{\partial}{\partial q_2} R_\theta \, \mathrm{d}q_2 = \mathrm{d}q_2$ to keep them honest. But then their predecessors (θ_1') with types $\theta_1' > \theta_1$ must also be paid $[F(\theta_2'|\theta_1) - F(\theta_2'|\theta_1')] \cdot \mathrm{d}q_2$ more, because retailer θ_1' is $[F(\theta_2'|\theta_1) - F(\theta_2'|\theta_1')]$ more likely than retailer θ_1 to reach condition $\theta_2' > \theta_2$. There are $\mathsf{P}(\theta_1' > \theta_1) = 1 - F(\theta_1)$ such retailers with the misreporting options. Hence, the manufacturer must increase the rent payment by

$$\text{rent increase} = \delta \cdot [1 - F(\theta_1)] \cdot [F(\theta_2'|\theta_1) - F(\theta_2'|\theta_1')] \cdot \, \mathrm{d}q_2. \tag{7}$$

At optimum, the manufacturer must justify the rent increase (7) by the surplus gain (6), resulting in the first-order condition for optimal quantity:

$$\begin{aligned} q_2^n(\theta^2) = {} & \underbrace{\frac{1}{2}(\theta_2 - c)}_{\text{static first-best}} \\ & \underbrace{- \frac{1}{2} \cdot \underbrace{\frac{1 - F(\theta_1)}{f(\theta_1)}}_{\text{inv. hazard rate } h(\theta_1)} \cdot \underbrace{\frac{F(\theta_2'|\theta_1) - F(\theta_2'|\theta_1')}{f(\theta_2|\theta_1)}}_{\text{carryover effect } \alpha}}_{\text{downward distortion } \frac{1}{2} h(\theta_1) \cdot \alpha} \\ = {} & \frac{1}{2}(\theta_2 - c) - \frac{1}{2} h(\theta_1)\alpha. \end{aligned}$$

We now identify $q_1^n(\theta_1)$. Consider an infinitesimal increase $\mathrm{d}q_1$ at θ_1. Without demand externalities ($\beta = 0$), the perturbation has only contemporary effects: the direct surplus gain $f(\theta_1)(\theta_1 - 2q_1^n - c)\,\mathrm{d}q_1$, and the indirect rent increase $[1 - F(\theta_1)]\,\mathrm{d}q_1$. Balancing them results in $q_1^n(\theta_1) = \frac{1}{2}(\theta_1 - c) - \frac{1}{2} h(\theta_1)$.

5.2. Regime $\mathcal{P}$: Dual Role of Demand Externalities

When demand externalities are salient ($\beta > 0$), the problem is more complicated. Besides misreporting, the retailer now can use initial sales q_1 to manipulate the future market $\theta_2 \sim F(\cdot\,|\theta_1, q_1)$ and his profits. In response, the manufacturer must recalibrate contract terms for each retailer. Let $\lambda(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[\pi_2(\theta^2)|\theta_1, q_1^*]$ and $\rho(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[\alpha h(\theta_1) q_2^*(\theta^2)|\theta_1, q_1^*]$. We find the following.

Proposition 3. *In regime $\mathcal{P}$,*

(a) *both parties benefit from better market condition:*

$$\frac{\partial}{\partial \theta_t} U_t(\theta^t) \geq 0, \qquad \frac{\partial}{\partial \theta_t} J_t(\theta^t) \geq 0, \qquad \forall t.$$

(b) *the optimal contract ϕ^* is*

$$\begin{aligned} q_2^*(\theta^2) &= \frac{1}{2}(\theta_2 - c) - \frac{1}{2} h(\theta_1)\alpha, \\ T_2^*(\theta^2) &= R(\theta_2, q_2^*(\theta^2)) - U_2^*(\theta^2), \\ q_1^*(\theta_1) &= \frac{1}{2}(\theta_1 - c) - \frac{1}{2} h(\theta_1) + \frac{\delta}{2}(\lambda(\theta_1) - \rho(\theta_1)), \\ T_1^*(\theta_1) &= R(\theta_1, q_1^*(\theta_1)) - U_1^*(\theta_1) + \delta \mathsf{E}[U_2^*(\theta^2)|\theta_1, q_1^*(\theta_1)], \end{aligned}$$

where $U_1^*(\theta_1) = \int_{\underline{\theta}}^{\theta_1} \mathsf{E}[q_1^*(\tilde{\theta}_1) + \delta\alpha q_2^*(\tilde{\theta}_1, \theta_2)\,|\tilde{\theta}_1, q_1^*(\tilde{\theta}_1)] \cdot \mathrm{d}\tilde{\theta}_1$ *and* $U_2^*(\theta^2) = \int_{\underline{\theta}}^{\theta_2} q_2^*(\theta_1, \tilde{\theta}_2) \cdot \mathrm{d}\tilde{\theta}_2$ *are the profits (information rent) for retailer θ_1 and θ^2.*

(c) *the optimal quantity for top retailer $\bar{\theta}$ is always efficient, $q_1^*(\bar{\theta}) = \bar{q}_1(\bar{\theta})$ and $q_2^*(\bar{\theta}, \theta_2) = \bar{q}_2(\bar{\theta}, \theta_2)$, $\forall \theta_2$; for other types $\theta_1 < \bar{\theta}$, it is bounded by $q_t^n(\theta^t) \leq q_t^*(\theta^t) \leq \bar{q}_t(\theta_t)$.*

In regime $\mathcal{P}$, the optimal contract ϕ^* must reconcile two *countervailing incentives*—to exploit demand externalities and to control information friction. It works as follows. Relative to the first-best $\bar{q}_1^n$ without demand externalities, the optimal quantity q_1^* employs two distortions. The *upward* adjustment $\frac{\delta}{2}\lambda(\theta_1)$ is productive, driven by the marginal gain from demand externalities, for the purpose of market growth; the *downward* distortion $\frac{1}{2}h(\theta_1)$ is unproductive, driven by precontract information θ_1, for the purpose of rent control; both distortions affect the distribution of the future market condition and hence the additional adjustment $\frac{1}{2}\delta\rho(\theta_1)$ for ensuring *future payoff wedges*. Depending on their relative strength, the net distortion $(q_t^* - \bar{q}_t^n)$ can go either downward or upward.

Proposition 3 reveals the dual role of demand externalities. (i) The first is the well-known *efficiency role*: By increasing market size, demand externalities can enhance channel surplus. The key policy response is to make upward adjustment early in the relationship, so that market size will grow with cumulative sales. (ii) The second is the novel *agency role*: By changing the distribution of the future market, demand externalities can either alleviate or exacerbate information friction. The policy response is more involved. The optimal quantity depends on how demand externalities shape the market condition: When they expand market gap $\Delta\theta_2$ between retailers, the manufacturer should limit demand externalities and distort sales downward; when they reduce the market gap, she should encourage growth and distort sales upward. In both cases, to control rent, the manufacturer should use demand externalities strategically.

For channel managers, a key question is when they can benefit from demand externalities. The conventional view suggests they should always benefit, because demand externalities can enhance surplus. This is indeed the case under full information (Proposition 1). Our view is more nuanced: Under asymmetric information, demand externalities are a double-edged sword. Although they can improve channel surplus by expanding market size (the efficiency role), they can also exacerbate information friction by enhancing the retailer's ability to extract rent (the agency role). To control rent inflation, the manufacturer may moderate demand externalities, hurting channel surplus. This tends to occur in the early stage of the relationship, when the information friction is still severe. Ignoring the dark side of the agency cost, however, previous studies may have overestimated the benefit of demand externalities.

6. Managerial Insights

We have shown that demand externalities can endogenize information asymmetry, induce countervailing incentives, and necessitate new responses. These structural results extend to arbitral periods with $K \geq 2$ (see Online Appendix E). We now examine two managerial implications of demand externalities.

6.1. Role of Private Information and Advance Selling

In the channel literature, a general insight is that private information breeds opportunism, suppresses output, and reduces surplus; hence, it is a main barrier for achieving channel coordination and the *first-best* efficiency.[17] Critically, this insight assumes all the private information θ_1 arrives *before* contracting and remains fixed over time. In practice, private information can also arise after contracting, and it can change over time. In regime $\mathcal{P}$, for example, demand externalities endogenize information asymmetry, allowing the retailer to learn *new information* ε_{t+1} after each round of selling q_t.[18] How does the new information $(\varepsilon_t)_{t\geq 2}$ change the channel performance?

There are two opposing arguments. (i) By the logic of adverse selection, the new information should worsen information asymmetry: It will raise information rent, aggravate output distortion, and exacerbate efficiency loss. Hence, the new information should benefit the retailer but hurt the manufacturer and the channel. (ii) Yet the result $\mathsf{E}U_1(\theta_1) = \mathsf{E}[U_1'(\theta_1)\cdot h(\theta_1)]$ reveals otherwise: Expected rent payment depends on initial θ_1 only, independent of $(\varepsilon_t)_{t\geq 2}$. This seems to implicate θ_1 but vindicate $(\varepsilon_t)_{t\geq 2}$: The new information should neither benefit the retailer nor hurt the manufacturer or the channel—it is *innocuous*.

Is the new information truly innocuous? To have a definitive answer, we now consider a new regime $\mathcal{P}^r$, in which initial θ_1 is private, but postcontract information $(\varepsilon_t)_{t\geq 2}$ is public:

$$J_1^r = \max\{\tilde{J}(\phi) : IR, IC_1\}. \qquad (\mathcal{P}^r)$$

Regime $\mathcal{P}^r$ arises, for example, when the manufacturer can mandate the disclosure of $(\varepsilon_t)_{t\geq 2}$, or the retailer can commit to sharing new information at the outset. It reduces information asymmetry to θ_1 only. Therefore, the manufacturer still needs to pay for screening θ_1, but she receives new information $(\varepsilon_t)_{t\geq 2}$ for free. Except the privacy of $(\varepsilon_t)_{t\geq 2}$, regime $\mathcal{P}^r$ is identical to $\mathcal{P}$. If the conventional wisdom were correct, that is, the privacy of $(\varepsilon_t)_{t\geq 2}$ indeed hurts, then in regime $\mathcal{P}^r$ with reduced information asymmetry, the retailer would extract less rent and the manufacturer would make more profits. Technically, the payoffs should differ because $\mathcal{P}^r$ *relaxes* future incentive constraints $(IC_t)_{t\geq 2}$. Yet we find the following.

Proposition 4. *The retailer makes the same profit in $\mathcal{P}^r$ and $\mathcal{P}$ and so does the manufacturer.*

This is revealing: Future incentive constraints $(IC_t)_{t\geq 2}$ have no bite—their *shadow price* is zero. As a result, (i) the retailer can extract the same amount of rent from initial information θ_1 alone (in $\mathcal{P}^r$), as he does from the entire process $(\theta_t)_{t\geq 1}$ (in $\mathcal{P}$); and (ii) the privacy of future information $(\varepsilon_t)_{t\geq 2}$ in $\mathcal{P}$ does not reduce efficiency. Although both initial θ_1 and future information $(\varepsilon_t)_{t\geq 2}$ can be private, the initial piece is far more consequential. Why?

The answer lies in the *timing* of the private information. In $\mathcal{P}$, the retailer observes θ_1 *before* contracting, so he is certain about his advantage and rent at the contracting stage. To screen the precontract information θ_1, the manufacturer has no choice but to pay the rent and distort sales; hence, efficiency suffers. By contrast, the retailer observes future ε_t only *after* contracting; before period t he is also uncertain about his future shock ε_t and the exact rent it can bring. Hence, he enjoys no real advantage from ε_t at the contracting stage. At the outset, the retailer still knows θ_t better than the manufacturer—conditional distribution $f^{t-1}(\theta_t|\theta_1)$ versus marginal distribution $f_t(\theta_t) \equiv \int f^{t-1}(\theta_t|\theta_1)\cdot f(\theta_1)\,\mathrm{d}\theta_1$; but that advantage flows from θ_1 and not ε_t. When the future t

arrives, the retailer can still gain after he observes ε_t; but the manufacturer can leverage his uncertainty of ε_t at time 1 to neutralize that gain, thereby screening future private information $(\varepsilon_t)_{t\geq 2}$ at no cost.

The screening device is *recursive advance selling*. In regime $\mathcal{P}$, to screen θ_t, the manufacturer must enforce IC_t with the payoff wedge between types θ_t and θ'_t—the technical origin of the information rent. In period 1, she has no choice but to pay the actual rent $U_1(\theta_1)$ for enforcing the wedge. Afterward, however, she has additional time dimension to enforce the wedge: She can advance-sell future output q_{t+1} in period t and refund later contingent on specific condition θ_{t+1}; the advance-selling price $\delta\mathsf{E}[U_{t+1}(\theta^{t+1})|\theta_t]$ is precisely the expected rent she will pay the retailer in period $t+1$. The resulting optimal payment can be decomposed into three terms (Online Appendix E):

$$T^*_t(\theta^t) = \underbrace{R(\theta_t, q^*_t(\theta^t))}_{\text{current sales}} + \underbrace{\delta\mathsf{E}[U^*_{t+1}(\theta^{t+1})|\theta_t, q^*_t(\theta^t)]}_{\text{advance sales}} - \underbrace{U^*_t(\theta^t)}_{\text{refund}}. \tag{8}$$

Advance selling indeed enforces truth-telling IC_t: As a constant shift, it keeps the payoff wedge $U^*_t(\theta^{t-1}, \theta_t) - U^*_t(\theta^{t-1}, \theta'_t)$ as required. Carrying out recursively, the manufacturer can extract $(\varepsilon_t)_{t\geq 2}$ for free.

Proposition 5. *In regime $\mathcal{P}$, the manufacturer should pay rent for θ_1 only; she can use recursive advance selling to extract new information for free.*

These results sharpen our understanding of private information. In static settings, the literature has a clear prediction: If the private information arises before contracting, it would hurt efficiency; if it arises after contracting, it need not hurt efficiency.[19] However, this static result rests on the simplistic assumption—*a single piece of exogenous* private information—which greatly limits its applicability. We extend it to dynamic settings, with *multiple pieces of endogenous* private information.

Beyond the generality, our results identify a new role of advance selling—screening. The extant literature rationalizes advance selling by price discrimination, demand uncertainty, and capacity constraints (Xie and Shugan 2009). We discover a new rationale: Advance selling can also serve as a screening device for eliciting private information sequentially. In our model, advance selling can achieve three objectives in one stroke: to coordinate the channel, to exploit demand externalities, and to screen private information. Although both output distortion and advance selling are screening devices, they differ in efficiency and applicability: Output distortion is less efficient but more applicable, as it can screen both pre- and postcontract information; by contrast, advance selling is more efficient but less applicable, as it can screen only postcontract private information.

6.2. How Do Demand Externalities Affect Long-Run Performance?

In the classic framework $\mathcal{P}^c$ with information asymmetry, a main prediction is that the first best is unattainable. Taking a static perspective, this prediction ignores *dynamic learning* in the relationship. Yet a real channel relationship often involves multiple interactions, through which both parties can learn about each other. Given this reality, one may conjecture that manufacturer learning should weaken the retailer's advantage, soften his temptation to manipulate, and dampen the distortion in the long run. When the relationship is sufficiently long, the manufacturer should be able to coordinate the channel, achieving the first best. Therefore, perpetual distortion should be an exception ($\alpha = 1$), not the rule: The classical second-best ϕ^c is unstable in the long run. We now formalize this conjecture.

Proposition 6. *In regime $\mathcal{P}$,*

(a) *the optimal contract ϕ^* converges to the first-best $\bar{\phi}$ in the long run.*

(b) *under ϕ^*, the market condition θ_t and sales q^*_t converge to steady-states θ_∞ and q_∞, which increase in carryover rate α and growth rate β. Moreover, if $\varepsilon_t \sim_{IID} \mathcal{N}(\mu, \sigma^2)$, then $\theta_t \to \theta_\infty \sim \mathcal{N}(\mu_{\theta_\infty}, \sigma^2_{\theta_\infty})$, and $q^*_t \to q_\infty \sim \mathcal{N}(\mu_{q_\infty}, \sigma^2_{q_\infty})$.*[20]

The proposition bridges the classical first- and second-best solutions. It deepens our understanding of optimal channel performance (under ϕ^*). (i) In the short run, it resembles the second best (under ϕ^c), because the information friction is severe initially; in the long run, it converges to the first best (under $\bar{\phi}$), because information friction vanishes eventually. (ii) The rate of convergence depends on market carryover rate α: The lower the carryover rate, the faster the convergence. The limit of convergence depends on the intensity of demand externalities: The higher the growth rate β, the higher the long-run limit. The extent of convergence depends on duration K: The longer the relationship, the smaller the distortion. When the market conditions are IID ($\alpha = 0$), the manufacturer can reach the first best as early as period 2; when the market is fixed ($\alpha = 1$), however, the distortion perpetuates. (iii) The classical solution ϕ^c is optimal only for the extreme case with constant market condition ($\alpha = 1, \beta = 0, \varepsilon_{t+1} \equiv 0$). To the extent normal markets can fluctuate over time, ϕ^c is suboptimal, unstable, even misleading for practical use. As we show in Online Appendix F, the efficiency loss can be substantial.

Proposition 6(a) has two policy implications. First, *when selecting a retailer, the manufacturer should prefer the incumbent*. This policy contrasts with the existing literature, which often views the preference as entrenchment, a defect to correct (Haucap et al. 2013).[21] We show the preference need not be defective; it has an efficiency justification: The manufacturer-side learning reduces information asymmetry and distortion; for the same market condition, the incumbent retailer demands less rent, sells more, and hence is more preferable.

Second, *when the market evolves over time, the manufacturer should neither pay rent nor distort production indefinitely*. Rather, it should tailor the contract to the business-specific carryover rate α and duration K. When market carryover is weak and the relationship is long, the manufacturer should distort sales and pay rent only initially; she should phase out both measures and adopt the first best eventually. The rationale is simple: Both measures are meant to neutralize the retailer's information advantage at the time of contracting; they are most effective in the early stage of the relationship, when the channel is most responsive to initial condition θ_1.

Proposition 6(b) characterizes the long-run trend of market condition and sales. The trend is mainly driven by two factors: The higher the market carryover α, the higher the growth rate β, and the higher the long-run trend (Figure 3). Tellingly, the prior $f(\theta_1)$—the key driver of the classical solution ϕ^c—has no effect in the long run. Figure 4 illustrates how the channel under ϕ^* evolves over time. It tracks 100 sample paths (envelope) $(\theta_t, q_t)_{t\geq 0}$ for two retailers, with initial conditions $\theta_1 = 28$ and 33.

We find that (i) *prior $f(\theta_1)$ is irrelevant in the long run*. Indeed, despite the huge gap of five in initial market condition, the low-type retailer catches up quickly. The market gap shrinks to one by period 4; by period 7, the two retailers are stochastically indistinguishable—They both have market size θ_∞ and sell q_∞. (ii) *The convergence to the first best is driven by market carryover and demand externalities*. Over time, the discriminatory treatment $\frac{1}{2}h(\theta_1)\alpha^{t-1}$ fades away; market carryover and demand externalities improve low-type retailers, but they can be insufficient to keep high-type retailer at his initial peak level. As a result, the retailers homogenize, the channel coordinates, and the performance gravitates toward the first best. (iii) *The manufacturer should take a long-term perspective*. This is because demand externalities imply *increasing returns* over time; internalizing them requires forward-looking calculation. The short-term concern of information asymmetry—the heart of the classical second-best ϕ^c—should not dictate the long-term goals of θ_∞ and q_∞.

7. Extensions

We now discuss four extensions.

7.1. When the Retailer Can Quit at Any Time

Our baseline model $\mathcal{P}$ only requires the participation constraint (IR) for the first period. Hence, quitting is not an option: Once in the relationship, the retailer must stay to the end. The solution ϕ^* is applicable in a legal environment where contracts are binding and can be enforced by a benevolent court of law. In a lesser environment, however, a retailer may have the option to quit the relationship. Does the solution ϕ^* still work?

It turns out that our solution still works, even when the retailer has the option to quit at any time of his choice. To formalize the case, we need to impose *dynamic participation constraints* $(IR_t)_{t=1}^K$ beyond the initial one:

$$U_t(\theta^t) \geq 0, \quad \forall \theta^t \in \Theta^t. \qquad (IR_t)$$

However, the optimal contract ϕ^* of $\mathcal{P}$ satisfies these constraints automatically: Indeed, the continuation profit for retailer θ^t is $U_t(\theta^t) = \int_{\underline{\theta}}^{\theta_t} \mathsf{E}[\sum_{\tau\geq t}\delta^{\tau-t}\alpha^{\tau-t}\cdot q_\tau^*(\theta^\tau) \mid \tilde{\theta}_t]\, d\tilde{\theta}_t \geq 0$, because all the order quantities are nonnegative. Hence, the contract ϕ^* remains optimal, even when the retailer can walk away at any time.

Figure 3. (Color online) Steady-State μ_{θ_∞} and μ_{q_∞}: $\alpha \in \{0, 0.1, 0.2, 0.3, 0.4\}$, $\beta \in [0, 0.3]$, $\delta = 0.9$, $\mu = 25$, $c = 3$

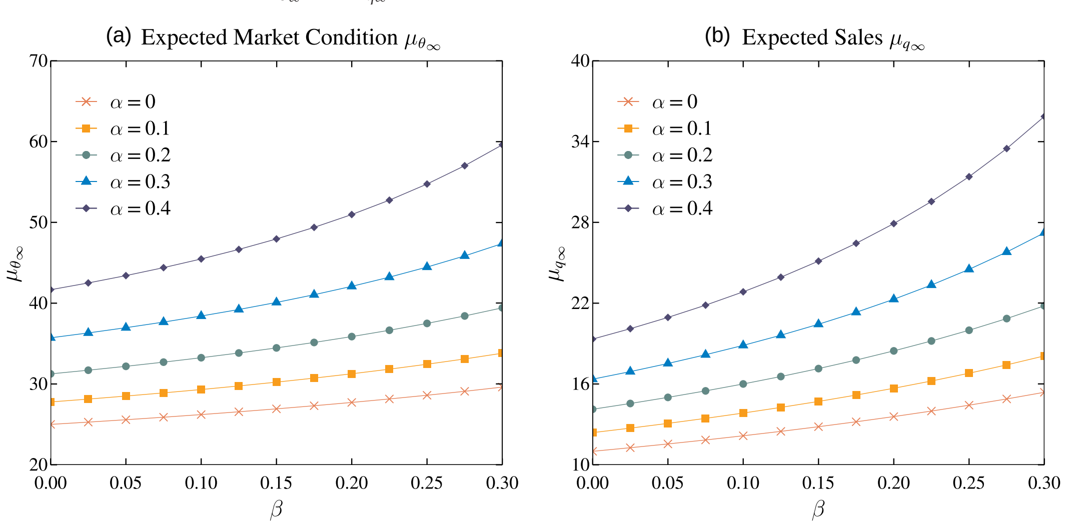
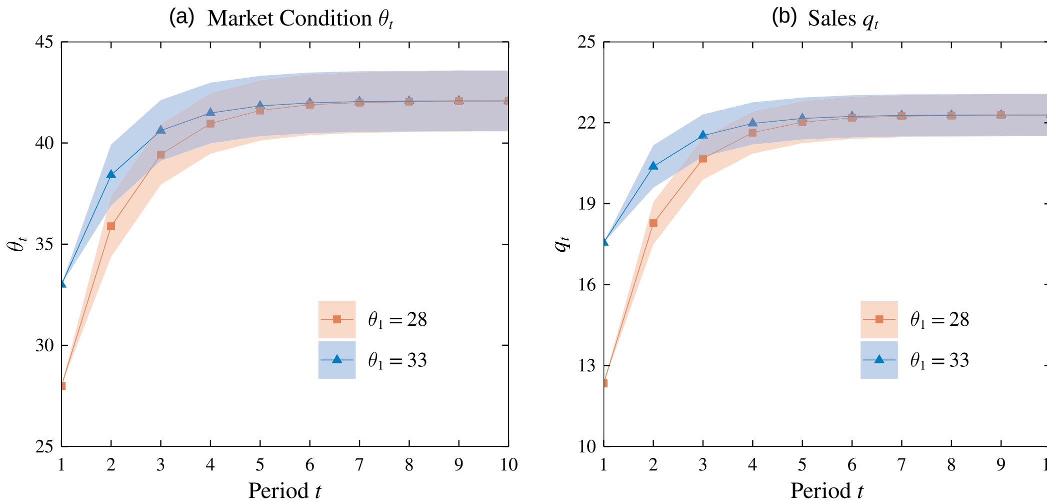


Figure 4. (Color online) Evolution of $(\theta_t, q_t)_{t\geq 1}$ over Time: $\alpha = 0.3$, $\beta = 0.2$, $\delta = 0.9$, $\mu = 25$, $\underline{\theta} = 27$, $c = 3$, $K = 20$



7.2. When the Carryover or Growth Rate Is Private

When the market condition θ_t is public but growth rate β is private, the problem reduces to static screening; the case for private carryover α is similar. To illustrate, consider a two-period model $\mathcal{P}_\beta$, where the retailer has private information (type) on the growth rate $\beta \in \mathcal{B} \equiv [\underline{\beta}, \bar{\beta}]$ with prior $\beta \sim F$. We focus on direct mechanisms $\phi = \{(q_t(\beta), T_t(\beta)) : \beta \in \mathcal{B}, t \leq K\}$ to screen β. Upon reporting $\hat{\beta}$, retailer β obtains the expected payoff $\tilde{U}_1(\hat{\beta};\beta) = (\theta_1 - q_1(\hat{\beta})) \cdot q_1(\hat{\beta}) - T_1(\hat{\beta}) + \delta \mathsf{E}[(\theta_2 - q_2(\hat{\beta})) \cdot q_2(\hat{\beta}) - T_2(\hat{\beta})]$. Let $U_1(\beta) \equiv \tilde{U}_1(\beta;\beta)$. The manufacturer solves the problem

$$\max_{\phi} \quad \{\mathsf{E}[T_1(\beta) - cq_1(\beta) + \delta(T_2(\beta) - cq_2(\beta))] : \\ U_1(\beta) \geq 0, \; U_1(\beta) \geq \tilde{U}_1(\hat{\beta};\beta), \; \forall \beta, \hat{\beta}\}, \qquad (\mathcal{P}_\beta)$$

where the constraints ensure participation and truthful reporting of β. We find the following.

Proposition 7. *In problem $\mathcal{P}_\beta$, the optimal solution ϕ^* is the classical second best, with*

$$q_1^*(\beta) = \frac{[2 + \alpha(\beta - h(\beta))\delta]\theta_1 + (\beta - h(\beta))\delta(\mu - c) - 2c}{4 - (\beta - h(\beta))^2\delta},$$

$$T_1^*(\beta) = R(\theta_1, q_1^*(\beta)) - \delta \int_{\underline{\beta}}^{\beta} q_1^*(\tilde{\beta}) q_2^*(\tilde{\beta}) \, \mathrm{d}\tilde{\beta}.$$

$$q_2^*(\beta) = \frac{[2\alpha + (\beta - h(\beta))]\theta_1 + 2\mu - [2 + (\beta - h(\beta))]c}{4 - (\beta - h(\beta))^2\delta},$$

$$T_2^*(\beta) = R(\alpha\theta_1 + \beta q_1^*(\beta) + \mu, q_2^*(\beta)).$$

The intuition is as follows. (i) To screen private information β, the manufacturer should pay the information rent $\delta \int_{\underline{\beta}}^{\beta} q_1^*(\tilde{\beta}) q_2^*(\tilde{\beta}) \, \mathrm{d}\tilde{\beta}$: The higher the growth rate β, the easier the manipulation, and the larger the information rent. The rent payment is one-shot, because private information is single piece. (ii) To reduce rents, the manufacturer should cut sales q_t^* from the first-best $\bar{q}_t$ for all but top retailer: The lower the growth rate (type) β, the higher the sales cut $(\bar{q}_1 - q_1^*)$. This discriminatory scheme arises because the sales cut reduces efficiency, and it is more efficient to cut sales for lower types and keep higher types sell near the first-best level.

7.3. Payment Schedule Implementation

Practitioners prefer simple implementations. In our problem, the optimal contract ϕ^* must resolve complex tradeoffs. Can it be implemented with commonly used instruments? We find the optimal menu of quantity-payment pairs $\{(q_t^*(\theta^t), T_t^*(\theta^t)) : \theta^t \in \Theta^t\}$ has a simple implementation of payment schedule $\hat{T}_t = \phi_t^*(\hat{q}_t)$, with marginal wholesale price $w_t(q) \equiv \frac{\mathrm{d}}{\mathrm{d}q}\phi_t^*(q)$ (the price for the qth unit). In particular, the schedule ϕ_t^* is a *quantity-discount* scheme if $\frac{\mathrm{d}}{\mathrm{d}q} w_t = \frac{\mathrm{d}^2}{\mathrm{d}q^2}\phi_t^*(q) < 0$, a *quantity-par* scheme if $\frac{\mathrm{d}}{\mathrm{d}q} w_t = 0$, and a quantity-premium scheme if $\frac{\mathrm{d}}{\mathrm{d}q} w_t > 0$.

Proposition 8. *In regime $\mathcal{P}^*$, the manufacturer can implement the optimal contracts $(\phi_t^*)_{t\geq 1}$ as a quantity-discount scheme.*[22]

Quantity discounts are common in practice. They are effective tools to alleviate double marginalization, price discriminate retailers, and mitigate demand uncertainty. Proposition 8 provides a stronger result: Quantity discounts can also emerge *endogenously* as an optimal response to dynamic private information. Intuitively, all retailers can sell the first few units, but the marginal value of additional units is decreasing, and the extent of the decrease depends on the retailer's private information θ_1. In response, the manufacturer should charge a higher price $w_1(q_1)$ for the first units and charge progressively lower prices for larger quantities. This quantity-discount scheme serves two purposes. First, it makes the low-quantity contract (intended for the low type) unattractive to the high-type retailer, thereby limiting the surplus the high type can extract. Second, it minimizes the quantity distortion (from the first best) for the high type, which is important because the higher the market condition, the higher the channel surplus.

7.4. Optimal Contracts for General Diffusion Dynamics and Revenue Function

We now consider the generalization $\mathcal{P}_g$ of the baseline model $\mathcal{P}$, with two new features. (i) The retailer's revenue function takes a general form $R^t(\theta_t, q_t)$: It is increasing in market condition θ_t, concave increasing in sales q_t, and supermodular in (θ_t, q_t).[23] (ii) The diffusion dynamics $\theta_2 = Z(\theta_1, q_1, \varepsilon)$ is nonlinear: It has carryover rate $Z_\theta \in [0,1)$ and growth rate $Z_q \geq 0$, with diminishing marginal effects of market conditions and demand externalities ($Z_{\theta\theta} \leq 0, Z_{qq} \leq 0$). For transparency, we focus on the two-period setup ($K = 2$).

The general model $\mathcal{P}_g$ has broader applications, for example, when consumers are strategic and social learning drives demand externalities (Online Appendix C). The model is also more complicated. To solve it, the manufacturer must compute how market conditions are intertemporally linked. Formally, let $\mathcal{E}(\theta^2, q_1) \equiv \{\varepsilon : \theta_2 = Z(\theta_1, q_1, \varepsilon)\}$ be the set of random market shocks that produce path $\theta^2 \equiv (\theta_1, \theta_2)$ under control q_1. Then we can define *carryover rate* by $Z_\theta(\theta^2, q_1) \equiv \mathsf{E}_\varepsilon[\frac{\partial}{\partial\theta_1} Z(\theta_1, q_1, \varepsilon) | \mathbb{1}_{\mathcal{E}(\theta^2, q_1)}]$, and the *growth rate* by $Z_q(\theta^2, q_1) \equiv \mathsf{E}_\varepsilon[\frac{\partial}{\partial q_1} Z(\theta_1, q_1, \varepsilon) | \mathbb{1}_{\mathcal{E}(\theta^2, q_1)}]$. They measure the marginal impact of current condition θ_1 and sales q_1 on future condition θ_2, along the path θ_1^2 under control q_1. For example, in the baseline model $\mathcal{P}$, the dynamics $\theta_2 = \alpha\theta_1 + \beta q_1 + \varepsilon$ is linear; hence, the carryover and growth rates degenerate to constant $Z_\theta \equiv \alpha$ and $Z_q \equiv \beta$.

Given contract $\phi_g = (q_t, T_t)_{t \leq 2}$, the retailer maximizes his expected payoff $\tilde{U}_2(\hat{\theta}^2; \theta^2) \equiv -T_2(\hat{\theta}^2) + R^2(\theta_2, q_2(\hat{\theta}^2))$, and $\tilde{U}_1(\hat{\theta}_1; \theta_1) \equiv -T_1(\hat{\theta}_1) + R^1(\theta_1, q_1(\hat{\theta}_1)) + \delta\mathsf{E}[U_2(\hat{\theta}_1, \theta_2) | \theta_1, q_1(\hat{\theta}_1)]$, where $U_t(\theta^t) \equiv \tilde{U}_t(\theta^t; \theta^t)$ is his equilibrium payoff. Anticipating this, the manufacturer solves

$$\max_{\phi_g \in \Phi} \tilde{J}(\phi_g) = \mathsf{E}[T_1(\theta_1) - c \cdot q_1(\theta_1) + \delta(T_2(\theta^2) - c \cdot q_2(\theta^2))], \quad (\mathcal{P}_g)$$

where $\Phi \equiv \{\phi_g : IR, IC_t, \ \forall t\}$ is the set of all feasible contracts. To state the solution, we define three functions: $\bar{\lambda}(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[R^2(\theta_2, \bar{q}_2(\theta_2)) - c\bar{q}_2(\theta_2) | \theta_1, \bar{q}_1(\theta_1)]$, $\lambda^*(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[R^2(\theta_2, q_2^*(\theta_2)) - cq_2^*(\theta_2) | \theta_1, q_1^*(\theta_1)]$, and $\rho^*(\theta_1) \equiv \frac{\partial}{\partial q_1} \mathsf{E}[h(\theta_1) \cdot Z_\theta(\theta^2, q_1^*(\theta_1)) \cdot R_\theta^2(\theta_2, q_2^*(\theta^2)) | \theta_1, q_1^*(\theta_1)]$. We find the following.

Proposition 9. *Consider the general cases,*

(a) *In regime $\bar{\mathcal{P}}_g$ with full information, the optimal contract $\bar{\phi}_g$ prescribes sales $\bar{q}_t$ by*

$$[R_q^1(\theta_1, \bar{q}_1(\theta_1)) - c] = -\delta\bar{\lambda}(\theta_1),$$
$$[R_q^2(\theta_2, \bar{q}_2(\theta_2)) - c] = 0,$$

and payments by $\bar{T}_t(\theta_t) = R^t(\theta_t, \bar{q}_t(\theta_t))$.

(b) *In regime $\mathcal{P}_g$ with information asymmetry, the optimal contract ϕ_g^* prescribes sales q_t^* by*

$$\underbrace{[R_q^1(\theta_1, q_1^*(\theta_1)) - c]}_{\text{marginal channel surplus}} = \underbrace{h(\theta_1) \cdot R_{\theta q}^1(\theta_1, q_1^*(\theta_1))}_{\text{distortion for screening } \theta_1} - \underbrace{\delta\lambda^*(\theta_1)}_{\text{distortion for externality gain } Z_q} + \underbrace{\delta\rho^*(\theta_1),}_{\text{distortion for market carryover } Z_\theta}$$

$$[R_q^2(\theta_2, q_2^*(\theta^2)) - c] = h(\theta_1) \cdot Z_\theta(\theta^2, q_1^*(\theta_1)) \cdot R_{\theta q}^2(\theta_2, q_2^*(\theta^2)), \quad (9)$$

and payments by

$$T_1^*(\theta_1) = \underbrace{R^1(\theta_1, q_1^*(\theta_1))}_{\text{current sales}} + \underbrace{\delta\mathsf{E}[U_2^*(\theta^2) | \theta_1, q_1^*(\theta_1)]}_{\text{advancesales}} - U_1^*(\theta_1), \ T_2^*(\theta^2) = R^2(\theta_2, q_2^*(\theta^2)) - \underbrace{U_2^*(\theta^2)}_{\text{refund}},$$

where $U_1^*(\theta_1) = \int_{\underline{\theta}}^{\theta_1} \mathsf{E}[R_\theta^1(\tilde{\theta}_1, q_1^*(\tilde{\theta}_1)) + \delta Z_\theta \ (\theta^2, q_1^*(\tilde{\theta}_1)) R_\theta^2(\theta_2, q_2^*(\tilde{\theta}_1, \theta_2)) | \tilde{\theta}_1, q_1^*(\tilde{\theta}_1)] \cdot d\tilde{\theta}_1$, *and* $U_2^*(\theta^2) = \int_{\underline{\theta}}^{\theta_2} R_\theta^2 (\tilde{\theta}_2, q_2^*(\theta_1, \tilde{\theta}_2)) \cdot d\tilde{\theta}_2$ *are the information rents for retailer θ_1 and θ^2.*

The proposition reveals three insights. (i) *The optimal contract ϕ_g^* still features advance selling, but the information rent U_1^* is complicated by nonlinear dynamics Z.* The carryover effect $Z_\theta(\theta^2, q_1^*)$ is now path and sales dependent, unlike the constant $Z_\theta \equiv \alpha$ in ϕ^* (Proposition 3). (ii) *The optimal contract ϕ_g^* must balance three competing motives*: to screen private information, to exploit demand externalities, and to prevent sequential manipulation. Relative to the static first best ($R_q(\theta, q) - c = 0$), it deploys three distortions in initial sales q_1^*: In Equation (9), the first distortion $h \cdot R_{\theta q}^1$ is downward for screening θ_1, the second distortion $\delta\lambda^* = \delta\mathsf{E}_1[Z_q \cdot R_\theta^2]$ is upward for exploiting demand externalities, and the last distortion $\delta\rho^* = \delta\mathsf{E}_1[h \cdot R_{\theta\theta}^2 \cdot Z_\theta \cdot Z_q + h \cdot R_\theta^2 \cdot Z_{\theta q}]$ is for preventing sequential manipulation. (iii) *Nonlinear dynamics can produce upward sales distortion, even beyond the first-best $\bar{q}_t$.* Unlike in regime $\mathcal{P}$ with linear dynamics ($Z_{\theta q} = 0$), the manufacturer in $\mathcal{P}_g$ can now leverage nonlinear dynamics to better manage retailer manipulation: Depending on the relative growth rate $Z_{\theta q}$, the distortion $\delta\rho^*$ can go either downward ($Z_{\theta q} > 0$) or upward ($Z_{\theta q} < 0$) and hence the overall sales distortion.[24] Therefore, to effectively manage the retailer, the manufacturer must consider both the bright and dark side of demand externalities.

8. Conclusion

Demand externalities are common in many retail markets. How should manufacturers manage such retail channels? We formulate the channel contracting problem as a dynamic game, where demand externalities can arise from either network effects or social learning. We find the optimal contract differs substantially from conventional ones. It is mainly driven by the interplay of information friction and demand externalities: to adapt to changing market conditions, it allows ex post adjustments for the best use of new information arriving over time; in the short run, it resembles the second-best, because information friction is still severe; in the long run, it converges to the first-best (adjusted for demand externalities) because information friction vanishes but demand externalities persist. Taking a dynamic-diffusion perspective, we establish a deep connection between the classical first- and second-best channel policies.

We find demand externalities can change the channel relationship profoundly. They induce countervailing incentives: Although demand externalities can improve channel efficiency by expanding market size, they can also exacerbate agency cost by enhancing the retailer's ability to manipulate markets. As a double-edged sword, the manufacturer should not promote demand externalities blindly: In the early stage of the relationship when the agency problem is still severe, the manufacturer should moderate demand externalities to control rent inflation. Ignoring the dark side of demand externalities, previous studies may have overestimated the benefits of demand externalities, especially in early stages of the relationship.

Our results provide practical guidance. (i) We identify when and why manufacturers should moderate demand externalities, overproduce output, offer advance selling, and favor incumbent retailers. (ii) We show private information per se does not hurt efficiency; its effects depend on the timing and nature of the interactions it entails. Through repeated interactions, both parties can learn from each other, reducing information friction. Ignoring such dynamic learning, previous studies may have overestimated the harm of information asymmetry. (iii) We show the optimal long-term contract can improve the classical second-best, by alleviating both growth and information efficiencies. The improvement can be substantial, when the channel relationship is durable and demand externalities are strong. By highlighting the dual role of demand externalities in long-run channel performance, this study deepens our understanding of channel theory and practice.

Endnotes

[1] We thank the associate editor for this insight.

[2] The notion of demand externalities is closed related to several concepts; for example, consumption externality (Berndt et al. 2003), adoption externality (Aoyagi 2013, Campbell et al. 2017), network externality (Tucker 2008), spillover effects (Geng et al. 2022), peer effects (Moretti 2011, Bailey et al. 2022), social contagion (Young 2009, Iyengar et al. 2011), social influence (Hu et al. 2016), social multiplier (Hartmann et al. 2008, Moretti 2011), neighborhood effects (Manski 2000, Graham 2018), and installed-base effects (Narayanan and Nair 2013). Following Xie and Sirbu (1995), we use the term *demand externalities* to encompass both social learning and network effects—the twin drivers of product diffusion (Nair 2019). Consistent with the diffusion literature, we focus on positive demand externalities (Peres et al. 2010). In certain markets, negative demand externalities can also arise, for example, from conspicuous consumption (Amaldoss and Jain 2005), herding, and information cascade (Banerjee 1992; Bikhchandani et al. 1992, 2021).

[3] Flipkart invested heavily in data and information technologies: It built the India's largest e-commerce big data platform (Dua 2018), which gives Flipkart a deep understanding of local consumer preferences, a crucial information advantage over Xiaomi.

[4] In India, WhatsApp is the main social media platform; By 2014, there were 600 million WhatsApp users and more than 1,000 Flipkart-specific WhatsApp groups (Dean 2023). For Flipkart's WhatsApp groups, see https://www.whatsgroup.in/flipkart-whatsapp-group-links. For Flipkart's online review and recommendation systems, see https://www.flipkart.com/mobiles/mi~brand/pr?sid=tyy,4io.

[5] Xiaomi's smartphones have both direct and indirect *network effects*. (i) Direct network effects arise, for example, because Xiaomi's users have extensive networks, enjoying lower learning cost and the ease of sharing files, photos, and music purchases. (ii) Indirect network effects also arise, because the smartphone OSs are platforms that connect smartphone users and app developers. Developers prefer to develop apps on OSs with more users, users are more likely to adopt OSs with more apps, and hence a positive feedback loop arises (Bresnahan et al. 2014, Liu and Luo 2023).

[6] Empirical studies on social learning are extensive; see Godes and Mayzlin (2004), Chevalier and Mayzlin (2006), Liu (2006), Manchanda et al. (2008), and Sorensen (2006). They find that word-of-mouth communication is often a significant part of consumers' valuation (Kumar et al. 2007), and it is often more credible and influential than the conventional advertising (Buttle 1998, Chen and Xie 2008, Mobius and Rosenblat 2014, Kuksov and Liao 2019).

[7] Empirical studies on network effects are enormous; see Farrell and Klemperer (2007), Liu and Chintagunta (2009), and Nair (2019) for comprehensive reviews.

[8] Advance selling is common in markets such as concerts, sports, cruises, group tours, educational programs, flights and trains, conferences, and trade shows; see Subramanian et al. (1999b), Chen (2001), Moe and Fader (2003), Tang et al. (2004), Li and Zhang (2013), Pang et al. (2021), Gale (1993), Dana (1998), Desiraju and Shugan (1999), Xie and Gerstner (2007), Zhao et al. (2016), Xie and Shugan (2001), and Fay and Xie (2010). For a comprehensive review, see Shugan and Xie (2000).

[9] The channel literature on information asymmetry is extensive; see Desai and Srinivasan (1995), Iyer (1998), Villas-Boas (1998), Desai (2000), Li (2002), Arya and Mittendorf (2004), Mishra and Prasad (2005), He et al. (2008), Gal-Or et al. (2008), Guo (2009), Guo and Iyer (2010), Dukes et al. (2011), Jiang et al. (2011), Mittendorf et al. (2013), Gao (2015b, 2021, 2024a), Jiang et al. (2016), Gao and Mishra (2019), Wang et al. (2019, 2020), and Akcay and Gao (2020).

[10] There is also a vast literature on information asymmetry; see Mirrlees (1971), Mussa and Rosen (1978), Maskin and Riley (1984), Baron and Besanko (1984), Laffont and Tirole (1986), Laffont (1993), Courty and Hao (2000), Battaglini (2005), Li and Gao (2008), Hwang et al. (2010), Xu et al. (2007), Gao et al. (2011, 2014a, b, 2017, 2020, 2024b), Pavan et al. (2014), Gao (2015a, 2023), Luo et al. (2016), Kuzu et al. (2019), and Zhang and et al. (2023). For book-length treatment, see Laffont and Martimort (2001) and Bolton and Dewatripont (2005).

[11] Methodologically, there are two types of models: *positive* and *normative* (Keynes 1897, Friedman 1953). They differ in scope, objective, and assumptions. Positive models *describe what is* and seek to *explain reality*; normative models *prescribe what ought to be* and seek to *improve reality*. Positive models dominate empirical studies, whereas normative models are common in theoretical works (Moorthy 1993). Both types of models are important to marketing research. Shugan (2005) pointed out that marketing research should not only *analyze the given rules* of the game (explain the reality) but also *design the new rules* for the game (e.g., use mechanism design to improve the reality).

[12] The lack of real-world examples for recursive advance selling should not be surprising: (i) recursive advancing selling is a feature of the *optimal equilibrium outcome*, not a *model assumption*; (ii) to our knowledge, neither researchers nor practitioners know what the optimal contract *ought to be*, let alone having implemented it in practice. As another example, Gale and Shapley (1962) find the *optimal policy*—the Gale–Shapley algorithm, or the deferred acceptance algorithm—for matching hospitals and residents; before 1962, however, it is unlikely to *observe* any real-world implementation of the Gale–Shapley algorithm.

[13] With certain modifications, our model can also apply to monopolistic screening in B2C markets, for example, for subscription services (Fudenberg and Villas-Boas 2006).

[14] U.S. law protects multiyear contracting, see Subpart 17.1. Special Contracting Methods of Multi-Year Contracting, https://www.acquisition.gov.

[15] See Arya and Mittendorf (2004, 2006), Arya et al. (2007), Taylor and Xiao (2010), Chen (2011), Xiong and Chen (2014), and Lai and Xiao (2017). Our model can also apply to monopolistic screening in B2C markets, for example, when subscription service contracts make long-term commitment possible (Fudenberg and Villas-Boas 2006).

[16] For example, the manufacturer can extract the entire channel surplus, whereas the retailer has no ability to make any profits. This prediction is hard to square with reality. Most retailers do make profits. For example, Apple's retailers enjoy 4.5% profit margin on iPhone X sales (Aulakh 2017); the video game retailers register 5% profit margin on Nintendo Switch consoles (Iggy 2017).

[17] The general insight that private information reduces efficiency has two versions (Bolton and Dewatripont 2005): In standard screening, the loss comes from information rents; in standard signaling, the loss comes from the separation effort. There are a few exceptions. Jiang et al. (2016) and Wang et al. (2019) show that information asymmetry can improve channel efficiency, through the offsetting mechanism of signaling and double marginalization. Because we do not restrict to wholesale contracts—the root cause of double marginalization—our model and insights are different.

[18] In period $t+1$, the market condition $\theta_{t+1} = \alpha\theta_t + \beta q_t + \varepsilon_{t+1}$ is the *cumulative information* that summarizes old information θ_t, fresh sales q_t, and *new information* ε_{t+1}.

[19] For example, Laffont and Martimort (2001, p. 58) show that, by making the retailer (agent) the "residual claimant," the manufacturer (principal) can achieve the first-best, extracting post-contract information at no cost.

[20] Specifically, $\mu_{\theta_\infty} = \frac{\beta d^* \mu - \beta b^* c + \mu}{1-(\alpha+\beta a^*)}$, $\mu_{q_\infty} = \frac{\beta d^* \mu - \beta b^* c + \mu}{1-(\alpha+\beta a^*)} a^* - b^* c + d^* \mu$, $\sigma^2_{q_\infty} = \frac{\sigma^2}{1-(\alpha+\beta a^*)^2}$, $\sigma^2_{\theta_\infty} = \frac{(a^*)^2\sigma^2}{1-(\alpha+\beta a^*)^2}$, $a^* = \frac{1-\delta\alpha^2 - \sqrt{[1-\delta\alpha^2][1-\delta(\alpha+\beta)^2]}}{\delta\beta^2+2\delta\alpha\beta}$, $b^* = \frac{1-\delta\alpha}{2-a^*(\delta\beta^2+2\delta\alpha\beta)+\delta\alpha\beta-\delta\beta-2\delta\alpha}$, and $d^* = \frac{a^*(\delta\beta+2\delta\alpha)-\delta\alpha}{2-a^*(\delta\beta^2+2\delta\alpha\beta)+\delta\alpha\beta-\delta\beta-2\delta\alpha}$.

[21] For example, Haucap et al. (2013) finds that incumbent retailers tend to have higher bargaining power and squeeze manufacturers' profits; in response, the squeezed manufacturers set higher wholesale prices for new retailers (waterbed effect), which hurts efficiency.

[22] In regime $\mathcal{P}^n$ without demand externalities, the manufacturer can implement the optimal contract ϕ_1^* as a quantity-discount scheme, and implement $(\phi_t^*)_{t\geq 2}$ as a quantity-par scheme.

[23] Formally, $R_\theta^t \equiv \frac{\partial}{\partial\theta_t} R^t(\theta_t, q_t) > 0$, $R_q^t \equiv \frac{\partial}{\partial q_t} R^t(\theta_t, q_t) > 0$, $R_{qq}^t \equiv \frac{\partial^2}{\partial q_t^2} R^t(\theta_t, q_t) < 0$ and $R_{\theta q}^t \equiv \frac{\partial^2}{\partial\theta_t q_t} R^t(\theta_t, q_t) > 0$.

[24] Specifically, the direction of distortion $\delta\rho^*$ depends on the relative relationship between $Z_{\theta q} R_\theta^2$ and $Z_\theta Z_q R_{\theta\theta}^2$: it is downward if $Z_\theta Z_q R_{\theta\theta}^2 > -Z_{\theta q} R_\theta^2$, and upward otherwise. The relative strength of the two distortions determines the net $hR_{\theta q}^1 + \delta\rho^*$: either upward or downward distortion is possible. The key is the relative growth rate $Z_{\theta q}$: when $Z_{\theta q} > 0$, the distortion is always downward ($q_1^*(\theta_1) \leq \bar{q}_1(\theta)$, $\forall\theta_1$); when $Z_{\theta q} < 0$ and $|Z_{\theta q}|$ is high enough such that $|Z_{\theta q}| > \frac{1}{R_\theta^2}(R_{\theta q}^1 + Z_\theta Z_q R_{\theta\theta}^2)$, the distortion can go upward, even beyond the first-best $\bar{q}_1$, despite information friction.

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