Influencing Adoption Patterns via Contract Structures in High-Tech Supply Chains

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Abstract

An original equipment manufacturer (OEM) who adopts a new technology or component product may bring various externalities to other OEM buyers and incentivize them to make similar adoption decisions. Positive correlation of adoptions can be harmful for the seller and buyers, as it can lead to adoption rush or delay, which results in demand-supply mismatch and may undermine the seller's ability to reinvest in R&D. Sellers thus would like to influence buyer behavior when introducing a new product. However, they often have little pricing power to implement effective intertemporal pricing strategies in supply chains in which prices are negotiated. We propose that sellers can influence buyer behavior through the structure of contract—i.e., a fixed- or renegotiable-price contract—and we support this by empirical analysis. Using a two-period, game-theoretic model, we find that (1) contract structure can affect the pace of adoption in different ways, and (2) the optimal contract choice depends on the strength of externality, the strength of seller competition, buyer bargaining power, and the size of buyer group.

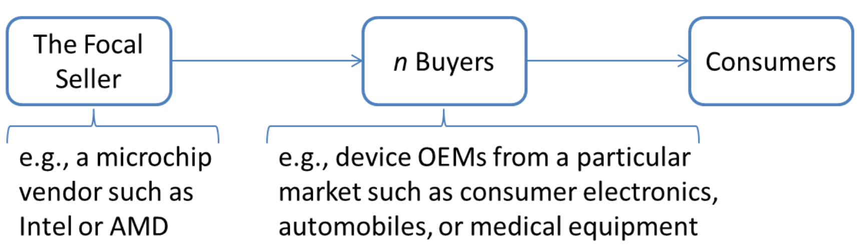
[*Keywords*: contract structure; product adoption; causal identification; externality; high-tech supply chain]

1 Introduction

When it comes to adopting a new technology or component product from a seller that supplies multiple buyers (as illustrated by Figure 1), a buyer's decision may bring various externalities to the system, affecting the payoffs and decisions of other buyers. According to previous research, there are at least three types of externality that are related to new product adoption. The first is known as the *learning curve effect* (Adler and Clark 1991; Irwin and Klenow 1994). For example, the unit production cost of semiconductor microchips significantly decreases with the cumulative output. This suggests that buyers could indirectly benefit each other as their adoptions lower seller cost and enable them to bargain for lower prices (Balachander and Srinivasan 1998). Second, the more widely a new component or technology is adopted, the more providers for compatible software, hardware, or services, thus forming a *network effect* (Katz and Shapiro 1985 and 1986), which benefits all the buyers. For example, the more widely a microcontroller is adopted, the more likely other manufacturers are to produce compatible components such as memories and sensors that augment the capabilities of the controller (Yadav and Singh 2004). In addition, many controllers must be programmed after purchase and more application-programming interfaces will support a controller if it is more widely adopted. Third, buyers may be unsure about the benefits and (design, production, and testing) costs associated with adopting a new product and one buyer's decision may influence the beliefs and decisions of others, resulting in an *informational externality* (Bikhchandani et al. 1992; Debo and Veeraraghavan 2009).

When such externalities exist, a buyer's incentive to purchase the focal product over time increases with the cumulative amount purchased by others, thus purchase quantities of different buyers in a given time period will be positively correlated. Positive correlation of buyers' adoptions

Figure 1: The system structure.



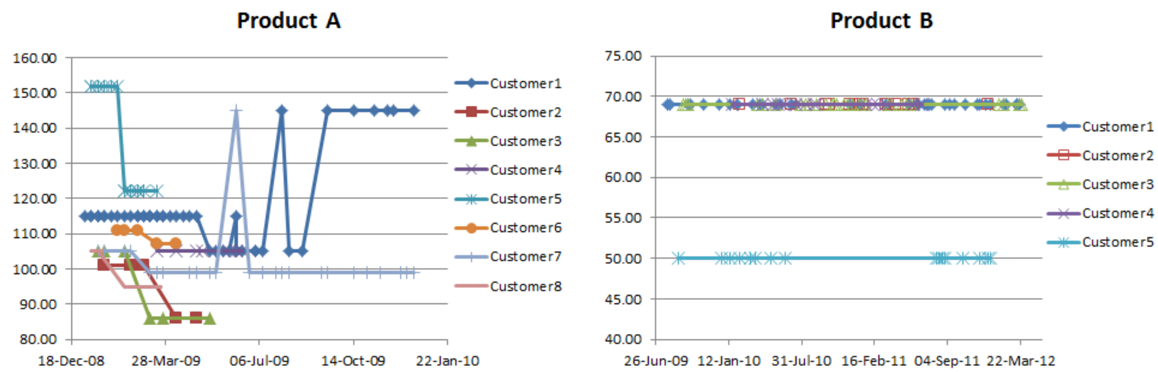
for a product can be harmful for the seller and the buyers, as it can lead to adoption rush or delay in equilibrium, which results in demand-supply mismatch in downstream markets and other inefficiencies. In particular, for high-tech, short life-cycle central processing unit (CPU) products, if OEMs (the buyers) build up their inventories too early, they then face demand uncertainty and expected mismatch costs may be passed on to the processor maker (the seller) through price negotiations. Conversely, if adoptions are too late, then both the OEMs and the processor maker miss early sales opportunities. In addition, a delay in adoptions potentially undermines sellers' cash flows and their ability to reinvest in research and development. Therefore, sellers should carefully influence buyer behavior when introducing a new product.

It is well known that in consumer markets, sellers frequently use intertemporal pricing strategies such as limited-time discounts or free trials (Xiong and Chen 2014) to spark adoption in early stages and control the process over time with price. However, in many business-to-business (B2B) markets, intertemporal pricing strategies may not be effective because sellers normally do not have absolute pricing power. Instead of dictating prices over time, sellers in industries such as semiconductor chips (Zhang et al. 2014), medical devices (Grennan 2013), airplanes (Garvin 1991), raw materials (Elyakime 2000), and services (Bajari et al. 2006) have to negotiate with buyers to settle prices. Hence, how sellers can control the pace of adoption in this case is an open question and we try to answer it in two steps.

In the first step, we examine and analyze sales data provided by a major microchip vendor. Empirically, we make four observations. (1) We show that the seller is using different types of contracts in terms of price flexibility (we call *contract structure*). In Figure 2, we show two typical price patterns for microchips sold to major buyers.[1] We can see that prices for product A were updated one or multiple times across its life cycle; for product B, prices for all five buyers were constant across the product life cycle regardless of how the quantities changed. (2) We construct measures for the contract structure and adoption pattern and show a correlation. We then show (3) that contract structures were not determined by the buyers and (4) that the contract structure influences buyer behavior (i.e., pace of adoption). To show these points, we devised an instrumental variable (IV) and performed a causal analysis. Based on our observations, we propose that sellers can influence buyers' adoption decisions through the structure of the procurement contract; i.e., a

[1] Note that buyers possessed different bargaining powers, so they received different prices through price bargaining.

Figure 2: Recorded transaction prices for two different products.



Note: Data is obtained from a major microchip vendor.

fixed- or renegotiable-price contract.

In the second step, given that the contract structure is a lever, we then study how the seller should best employ it. Using a two-period, game-theoretic model, we analyze the impact of contract choice on buyer behavior as well as on the pace of product adoption in a B2B market with the existence of positive externalities. In this model, we consider the following factors: (*i*) demand uncertainty and demand learning; (*ii*) adoption-independent demand potential; (*iii*) adoption-dependent valuation for the buyers; (*iv*) adoption-dependent cost learning for the seller; and (*v*) strategic price bargaining between the seller and the buyers. Our model helps us understand the incentives associated with different structures of contracts, and our analysis reveals the following interesting but unintuitive results.

- Compared to a renegotiable price, a fixed-price contract can lead to faster adoption in some cases but slower adoption in others.

- The choice between a fixed and renegotiable price depends on the strength of externality, the strength of competition from alternative technologies or products, the relative bargaining power of the buyer, and the size of the buyer group (i.e., the scale of the "network").

Our work is related to the stream of literature that studies product / technology diffusion-process management. However, the topic of our paper, product diffusion-process management in high-tech supply chains through the choice of contract structure, has not been well investigated. Most research on product diffusion is based on the Bass model (Bass 1969). Robinson and Lakhani (1975) conducted the first study of a dynamic pricing problem of a seller who faces a price-dependent demand process that is represented by an extended Bass model. Under a similar framework, Kalish and Lilien (1983) studied optimal government subsidy policies for promoting the adoption of a new energy source. Krishnan et al. (1999) then proposed the generalized Bass model and developed an optimal pricing path that is consistent with empirical data. More recently, Ho et al. (2002), and Kumar and Swaminathan (2003) studied the management of demand and sales dynamics in the new product diffusion process under supply constraint: in their models, a seller can turn down the request of a customer who then either waits or exits the market.

Our study is distinct from this stream of research in the following ways. First, customer behavior is different. While most of the previous research focuses on product adoption in consumer markets and assumes buyers are non-strategic, we focus on business-to-business markets and empirically find that buyer behavior is significantly dependent on the price mechanism and other buyers' decisions. Second, the management lever is different. Previous research normally assumes that the seller has the pricing power and thus could employ intertemporal pricing strategies to influence buyer behavior; in contrast, we consider markets in which prices are subject to negotiations, and we propose contract choice in terms of price flexibility as a lever. Third, the problem focus is different. Previous research uses the Bass model for the demand process and assume that the market potential is known and fixed; the focus is on problems such as optimal pricing strategy and supply constraints. However, we assume that the demand potential in the end market is unknown and can be learned over time and we focus on how to minimize the cost of demand-supply mismatch in a two-echelon supply chain system, where positive externalities of adoption exist. Finally, we use real data to show that the choice of contract-price flexibility can serve as an effective lever for managing product adoption in high-tech supply chains.

Papers that explicitly consider positive externalities in the product-adoption process normally do not use the Bass model but assume that buyers are strategic. Katz and Shapiro (1986) study the network effect in the product-diffusion process and focus on competitive equilibrium in the market. Balachander and Srinivasan (1998) study the learning curve effect in new product introduction and focus on the optimal introductory pricing strategy. Our research is different because we consider demand uncertainty and price negotiation and we focus on contract choice. In addition, while the network effect studied in previous research benefits end consumers, we consider network externalities that only impact the buyers (e.g., OEMs), which we call *intermediary good network externality.* Our interactions with sales and procurement managers in high-tech supply chains suggest that thousands of products are introduced into B2B supply chains each year that experience intermediary good network externalities of the kind assumed here.

2 Empirical Investigation

In this section, we employ empirical analysis to show that, in an industry where both fixed- and renegotiable-price contracts are frequently used, buyers' product adoption decisions are influenced by contract structure chosen by sellers. To do so, we propose measures that represent contract structure and adoption pattern respectively, and explore the correlation between the measures. Next, we use an instrumental variable to establish the causal relation between contract structure and adoption pattern. In addition, we show that adoption patterns are positively correlated among buyers, which supports the fact that product adoption generates positive externalities.

2.1 Data Description

For this study, a major global microprocessor maker supplied sales data encompassing 3,826 products and 251 customers over a three-year period. Each entry of this dataset consisted of a customer ID, product ID, product category, subcategory, sales territory, bill quantity, unit price, and date of transaction. Let I_C and I_P be the indices of customer and product, respectively. We define an *instance* θ_{ij} as the set of purchase (price-quantity) records related to a customer i and a product j, where $i \in I_C$ and $j \in I_P$. Let $\mathcal{T}_{ij}$ be the set of dates at which customer i purchased product j. Then let q_{ijt} and p_{ijt} denote the transaction quantity and price for customer i and product j at time $t \in \mathcal{T}_{ij}$. Hence, an instance is defined as

$$\theta_{ij} := \{(t, q_{ijt}, p_{ijt}) : t \in \mathcal{T}_{ij}\}.$$

Notice that the influence of contract structure extends across the entire life span of an instance, and that any single transaction offers little relevant information. Hence, we examine data aggregated at

Table 1: Instance-Level Summary Statistics

	Mean	S.D.	Min	Max
Initial Price ($)	126	200	0.01	2,625
Total Quantity	59×10^3	266×10^3	101	8.2×10^6
Total Value ($)	1.8×10^6	5.8×10^6	30	132×10^6
Duration (days)	306	266	7	1,179
ACVP†	0.53	16	0	1,284
TDPS‡	0.61	0.26	0.01	1.00
Dist. of ACVP	≤ 0	≤ 0.05	≤ 0.5	Total
# of Instances	4452	6353	9603	9,773

† *ACVP* is a measure of price flexibility. The median is 7.48×10^{-4}.

‡ *TDPS* is a measure of adoption pattern.

instance level. In addition, let ω_i be the vector of characteristics that are exogenous for customer $i \in I_C$, and let π_j be the vector of characteristics that are exogenous for product $j \in I_P$. For customers, exogenous characteristics ω include the total purchase value with the seller over the three years (the "size") and the geographic location. For products, exogenous characteristics π may include the number of customers buying the product and the product category. Define $\Omega := \{\omega_i : i \in I_C\}$, $\Pi := \{\pi_j : j \in I_P\}$, and $\Theta := \{\theta_{ij} : i \in I_C, j \in I_P\}$. In this way, the dataset can be summarized as $\mathcal{D} := \{\Omega, \Pi, \Theta\}$.

The instance-level summary statistics are shown in Table 1, where ACVP and TDPS are defined later as measures for price flexibility and adoption pattern, respectively. In particular, we have ACVP > 0 if a price change is recorded for an instance; otherwise, we view an instance with ACVP $= 0$ as being under a fixed-price contract. As shown in Table 1, nearly half of the instances are with fixed-price contracts. This means that both fixed- and renegotiable-price contracts were frequently used, and provides us with an opportunity to test the impact of contract structure.

2.2 Measures

In the following, we propose measures for contract structure and adoption pattern, respectively.

Contract Structure. The dataset does not give information about the underlying contract structure φ for each instance. Thus, we have to uncover φ from the data. However, it is important to note that in practice, contract choice for price flexibility is hardly a binary one. For example, sellers may allow price renegotiations, but restrict the range of price variations or degree of price flexibility by properly designing the contract. Buyers' adoption patterns may depend on the degree of price flexibility. Therefore, we propose a continuous measure for the degree of price flexibility in this paper: the adjusted coefficient of variation (CV) of price (ACVP), which is defined as the standard deviation of price divided by the initial price of an instance. Mathematically,

$$\text{ACVP}_{ij} := \frac{\sqrt{\frac{1}{|\mathcal{T}_{ij}|-1}\sum_{t\in\mathcal{T}_{ij}}\left(p_{ijt} - \frac{1}{|\mathcal{T}_{ij}|}\sum_{k\in\mathcal{T}_{ij}} p_{ijk}\right)^2}}{p_{ij(\min\mathcal{T}_{ij})}}. \tag{1}$$

Other possible candidates to measure φ include: (i) the average duration of a price, (ii) the variance of price, and (iii) the CV of price. However, in the Appendix, we point out the problems with these measures, and thus we adopt the ACVP. Note that instances having only one transaction contain no information about the underlying price mechanism, so those instances are deleted from $\mathcal{D}$.

Adoption Pattern. The adoption pattern is basically the pace of adoption, which is manifested in how purchases are made over time. If a buyer decides to slow down the adoption process, the effects are mainly twofold. First, the *duration* of an instance may be prolonged, given the same total amount of purchase. Second, the intertemporal distribution of purchase quantity of an instance will be right-skewed along the time axis (skewed towards the future). To measure the pace of adoption, we introduce the time-discounted percentage sales (TDPS) of an instance, using the first date of the instance as the time reference. Mathematically, we have

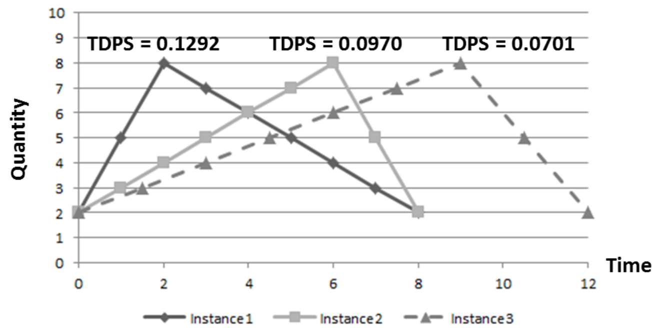
$$\text{TDPS}_{ij} \quad := \quad \sum_{t\in\mathcal{T}_{ij}} q_{ijt}\cdot e^{r(\min\mathcal{T}_{ij}-t)} / \sum_{t\in\mathcal{T}_{ij}} q_{ijt}, \tag{2}$$

where r controls the time weights of this measure.[2] Notice that the TDPS is equivalent to the Laplace transform of the purchase-quantity distribution over time, so comparing it means ranking quantity distribution in the Laplace transform order. Figure 3 illustrates the TDPS meaning.

In Figure 3, the pattern of instance 1 serves as a benchmark. Compared with instance 1, instance 2 has the same total amount of purchase but have large orders placed at a later stage so that the

[2] In this research, we carefully set $r = 2$ per year to ensure that the TDPS is an effective measure.

Figure 3: Fictitious instances with different adoption patterns.



pattern is right-skewed. In instance 3, for the same amount in each purchase as in instance 2, the buyer deferred all the purchases so that the pattern is scaled up along the time axis compared with the second one. Hence, the TDPSs for these three instances are in decreasing order.

2.3 Correlation and Causal Analysis

Our goal is to uncover the relation between the true but unobservable variables—contract structure and adoption pattern—by investigating the relation between the ACVP and TDPS. Considering that the total quantity (TQ) of an instance is the only observed factor that could have a common influence on the ACVP and TDPS,[3] we run the regression:

$$TDPS = a_0 + a_1 \cdot ACVP + a_2 \cdot \mathbb{I}\{ACVP = 0\} + a_3 \cdot TQ + \epsilon, \tag{3}$$

where $\mathbb{I}\{ACVP = 0\}$ indicates whether a fixed-price contract is used.[4] We obtain estimates $\hat{a_1} = -0.036$ with a P-value 0.0038, $\hat{a_2} = 0.167$ with a P-value 0, and R^2 of 0.136. The residuals are uncorrelated with the ACVP and the estimates are consistent. The results imply that if the TDPS of an instance is around 0.61 (the average), then the change of contract structure from fixed-price to renegotiable-price will be associated with a delay of nearly *two month for each purchase*, which is very meaningful for microchips. The relationship between contract structure and purchase pattern is impacted by a number of unobservable variables including demand shocks and

[3]Prices are more flexible for larger deals, and durations are longer for instances with larger quantities.

[4]Note that the ACVP is bounded by 0 and according to Table 1 nearly half of the instances have a fixed-price contract (i.e., ACVP = 0). Thus, a simple linear relation without the contract type being controlled is not appropriate.

product and firm specific factors. Also the ACVP and TDPS are approximations for the contract structure and purchase pattern. These factors contribute to low R^2. The focus of our analysis is on uncovering a relationship between the contract structure and purchase patterns and not on developing a prediction model. The low P values establish that the relationship is statistically significant.[5]

The following lists alternative casual hypotheses for the correlation between the ACVP and TDPS.[6]

Hypothesis (I). The contract structure causes adoption pattern; i.e., buyers respond strategically to the degree of price flexibility. For example, it is likely that buyers tend to delay their purchases when prices are renegotiable. If this is the case, contract choice should be a useful lever for sellers to control product-adoption processes.

Hypothesis (II). The purchase pattern of each instance is exogenous, and the seller or the buyer designed the contract structure based on this pattern. For example, the seller may offer a discount to a buyer if product adoption was slow at early stage, or, if a buyer knew that larger quantities would be purchased at later stage, she might prefer a contract with a flexible price so that a lower price could later be negotiated. Another scenario may be that buyers have been strategically controlling their adoption patterns to influence the price regardless of the initial contract choice. Whichever is the case, the degree of price flexibility is caused by the adoption pattern, and *ex-ante* contract choice is not useful.

Hypothesis (III). Price flexibility and adoption pattern are commonly caused by a set of unobservable variables ε (e.g., price flexibility and adoption pattern are jointly determined by buyers, by product-specific market norm, or by a general trend over time).

Hypothesis (IV). The measures ACVP and TDPS are commonly influenced by the duration of an instance. The TDPS is by definition dependent on the duration, which is a part of the adoption

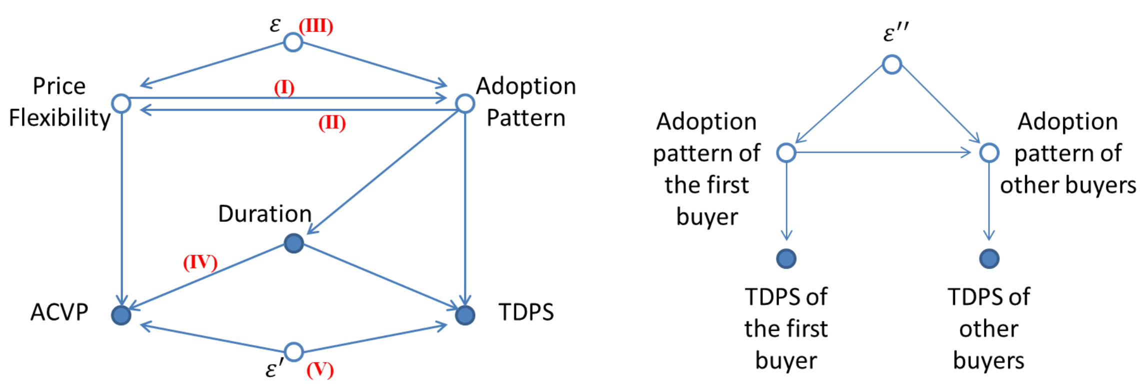
[5] Note that high R^2 is normally not required for causal analysis (e.g., Ichino and Winter-Ebmer 1999; Glaeser et al. 2004).

[6] Following Reiss (2005), we assume that: Any two variables X and Y are correlated if and only if either (i) X causes Y, (ii) Y cause X, (iii) a common cause Z causes both X and Y, or (iv) any combination of (i)–(iii). Because the ACVP and TDPS are just measures, (i) and (ii) do not apply. Also, we assume the *transitivity* of causal relations holds: For any three variables X, Y, and Z, if X causes Y and Y causes Z, then X causes Z.

pattern. However, there is no guarantee that the ACVP is directly affected by the duration of an instance. In addition, it is important to note that the ACVP could be correlated with duration even if there is not a direct link between the two; e.g., they could be commonly caused by the adoption pattern given (II) is true.

Hypothesis (V). The measures ACVP and TDPS are commonly influenced by a set of unobservable variables ε', which may include buyer-specific, product-specific, or time-related factors.

Figure 4: Possible causal relations.



Note: A circle represents an unobservable variable, a solid dot represents an observable variable, and a directed edge represents a causal relation with the edge pointing from the cause to the result.

All of the possible causal relations are summarized and illustrated on the left of Figure 4. Here, we propose an IV that can be used to test the possible causal relations. Thanks to the seller's learning-by-doing and the existence of other possible externalities, buyers may respond directly to adoption decisions of other buyers, especially those who adopt earlier. Even if purchase information is privy to each buyer, it is still very likely that purchase decisions are highly correlated among buyers due to some common causes. As a result, we separate the first buyer of a product from the rest and use the TDPS of the first buyer to generate an instrumental variable to test the relation between the ACVP and TDPS for other buyers of this product. The possible causal relations are shown on the right of Figure 4.

2.4 Test of Hypotheses

In preparation, we delete data for products with only one buyer and 13 instances with an ACVP greater than 10 (abnormally large). In addition, to avoid the truncation effect in this dataset, we only include instances with an observed starting date at least one month later than the starting date of the dataset and an observed ending date at least one month earlier than the ending date of the dataset. We then run regressions (a), (b), and (c). The results are summarized in Table 2.

Table 2: Tests of Correlations With the Instrumental Variable

Regression	$\hat{\gamma}$	*P-value*
(a) $Y = \gamma_a \cdot X + \epsilon_a$	0.3575	1.3×10^{-181}
(b) $Y = \gamma_b \cdot Z + \lambda_b \cdot \mathbb{I}\{Z = 0\} + \mu_b \cdot TQ + \epsilon_b$	-0.0517	7.9×10^{-4}
(c) $X = \gamma_c \cdot Z + \lambda_c \cdot \mathbb{I}\{Z = 0\} + \mu_c \cdot TQ + \epsilon_c$	0.0369	0.9798

Note: There are in total 5,652 observations. P-values are for one-sided tests.
X: TDPS for the first buyer of a product.
Y: TDPS for a buyer who is not the first buyer of a product.
Z: ACVP for a buyer who is not the first buyer of a product.

Regression (a). We regress the TDPS of a buyer who is not the first buyer against the TDPS of the first buyer. We have a *positive* correlation with a significant P-value. This means that adoption patterns among the buyers are positively correlated, possibly due to the positive externalities.

Regression (b). We regress the TDPS against the ACVP for a buyer who is not the first one, with the contract type and the total purchase quantity of the instance controlled. We have a *negative* correlation with a significant P-value. This regression is similar to the one with the full dataset, and it suggests the existence of causal relations.

Regression (c). We regress the TDPS of the first buyer against the ACVP of a buyer who is not the first one for that product, with the contract type and the total purchase quantity controlled. We have no significant negative correlation. However, if hypothesis (I) is not true, we would have obtained a negative correlation as discussed in the following.

First, suppose (II) or (IV) or both are true. In other words, the TDPS and the ACVP are commonly influenced by the adoption pattern. In this case, the TDPS of the first buyer (X), the TDPS (Y) and the ACVP (Z) for a buyer who is not the first should be commonly influenced by the adoption pattern of the first buyer or by some factor ε''. Regressions (a) and (b) suggest X and Z should be negatively correlated. However, (c) shows that this is not supported by the data.

Second, suppose (III) or (V) or both are true. As broadly as we can imagine, the unobservable factors ε and ε' can only come from three sources: product-specific factors, buyer-specific factors, or some market- or technology-related trends. We test them in sequence.

- If ε and ε' are product-specific characteristics, such as supply-side or demand-side competition, life-span, grade, or usage among others, then all the buyers buying a product are subject to the same impact; i.e., ε and ε' should influence all the buyers of a product. As a result, X, Y, and Z should be commonly influenced and thus correlated. However, this is not supported by regression (c).

- If ε and ε' are time-related factors, then all the buyers buying in the same period are subject to the same impact. We learn from the data that the average time lag between a buyer's first purchase of a product and the first-ever purchase of that product is less than a quarter. Thus, the first buyer of a product should be viewed as being in the same period as subsequent buyers. As a result, X, Y, and Z should be commonly caused and thus correlated. However, this is not supported by (c).

- Given our previous arguments, ε and ε' can only be buyer-specific characteristics. If this is the case and (I) is not true, then the correlation between the ACVP and the TDPS with total quantity controlled should not exist conditioning on a specific buyer. However, we show that this is not true (in the Appendix). The correlation suggests that contracts were not offered by buyers; otherwise, buyers would have selected contracts to fit their situations, rendering contract structure and adoption pattern commonly caused by buyer type.[7]

Finally, to close the loop and confirm hypothesis (I), we can use the correlation between the ACVPs of the first and a subsequent buyer, which is due to the seller's contract preference, and apply a

[7]Let q_i denote the purchase profile of buyer i, and $u_i(q_i, \varphi)$ the payoff. If the contract is offered by buyers, then buyer i would choose contract $\varphi_i = \arg\max_{q_i,\varphi} u_i(q_i, \varphi)$, which suggests that φ should be a function of buyer type. Although we cannot directly prove that contracts were indeed offered by the seller, it is very likely the case given that there was no third parties who offered the contract.

similar IV method: regress the TDPS of the buyer who is not the first one against the ACVP of the first buyer for that product with the contract type and the total purchase quantity controlled. We obtain a coefficient -0.044 with P-value 0.0735, implying a negative correlation. As a result, we claim that *contract structure influences adoption pattern; i.e., buyers respond to the contract structure by intertemporally shifting their purchase quantities.*

2.5 Discussions

To arrive at the above causal relation, we have employed an approach that is different from traditional methods such as direct *regression* of buyer behavior against contract structure. Due to the nature of the problem we are examining, direct regression is not effective. First, direct regression cannot identify causal directions. Second, to estimate causal effects through direct regression, all the possible common causes have to be controlled simultaneously, many of which are unobservable, and we cannot reject the existence of the possible common causes. In addition, it is hard to find an instrumental variable that is independent of all of the unobservable variables. In contrast, our approach is immune to all these concerns. In particular, our approach is to rule out one alternative hypothesis at a time, and thus we do not need to simultaneously test all the alternative hypotheses.

The causal relation we just observed suggests that the contract structure is an effective lever to influence buyer behavior in the product-adoption process, at least for a major seller in the semiconductor industry. Several questions immediately emerge: Does renegotiable price always lead to late adoption? Is faster adoption always preferable? How should the seller pick the contract? To gain a deeper understanding, we develop a model to understand how price flexibility and contract structure would affect buyer behavior in different situations.

3 The Model

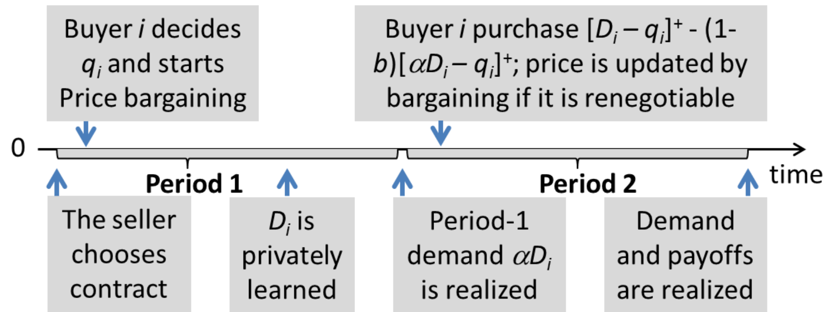
Now we build a stylized model and make the following key assumptions. (i) The seller makes the choice between fixed- and renegotiable-price contracts. (ii) Buyers make quantity decisions after the contract type is determined. (iii) Buyers face uncertain demand and they learn about demand over time. (iv) The demand potential is independent of product adoption. (v) The unit production cost for the seller is decreasing with the cumulative production quantity. (vi) Product adoption influences buyers' valuation for the focal product. (*vii*) Prices are negotiated.

Market Characteristics: Consider a seller (he) that produces a (component) product X and sells it to n buyers in two periods.[8] Let $N = \{1, 2, ..., n\}$ be the set of the indices for the buyers, and "0" index the seller. The buyers use product X to produce similar but differentiated (or at least branded) final products. Each unit of final product consumes one unit of product X. To make the seller's problem tractable, we abstract from direct competition among the buyers and their pricing problems in the end market. We assume that the total demand potential D_i for buyer i is exogenously given. $\tilde{D} := (D_1, \ldots, D_n)$ is unknow *ex ante*, but follows prior joint distribution F, which is common knowledge. The marginal distribution F_i has a compact support $[0, M_i]$. Demand D_i will be realized over two periods: $\alpha_i D_i$ in period 1 and $(1 - \alpha_i)D_i$ in period 2, where $\alpha_i \in (0, 1)$ for any i is publicly known, plausibly due to known product-diffusion patterns. We model demand learning by assuming that D_i will be observed by buyer i during period 1. Note that brand-choice-based product substitution in the end market is captured by the joint distribution F. However, for the sake of tractability, we ignore stockout-based substitution among the final products. In case of stockout in period 1, we assume that a fraction $b \in [0, 1]$ of the unsatisfied demand will be backlogged and satisfied by priority in period 2 and the rest will exit the market.

Adoption Decisions: Buyers can purchase product X in both periods. Holding cost for excess purchases is ignored. Let q_i and fq_i denote purchase quantity of buyer i in period 1 and period 2, respectively. Moreover, let d_{it} and s_{it} denote the demand and sales of buyer i in period t, respectively. Then we have $s_{i1} = \min\{q_i, d_{i1}\} = \min\{q_i, \alpha_i D_i\}$ and $s_{i2} = d_{i2}$, because demand is known to i in period 2. In particular, the total demand in period 2 is the sum of backlogged demand and newly realized demand—i.e., $d_{i2} = b\left[\alpha_i D_i - q_i\right]^+ + (1 - \alpha_i)D_i$, where $x^+ := \max\{0, x\}$—and the purchase quantity $fq_i = \left[d_{i2} - [q_i - \alpha_i D_i]^+\right]^+$ just fills the gap between demand and existing capacity for a rational buyer. The following lemma transforms fq_i from a complicated function to the difference of two simple convex functions, and it provides an expression for the amount of excess capacity that is carried over and used in period 2. Note that $x \wedge y := \min\{x, y\}$.

[8] A two-period model sufficiently captures the dynamics of our problem, and the finite horizon reflects that the product has a limited market window, possibly because of advances in technology or changes in consumer tastes. Such a setting is consistent with papers that study product adoption with positive externalities and strategic buyers, e.g., Katz and Shapiro (1986) and Balachander and Srinivasan (1998).

Figure 5: Sequence of events.



Lemma 1. $fq_i = [D_i - q_i]^+ - (1-b) \cdot [\alpha_i D_i - q_i]^+$ *and* $s_{i2} - fq_i = D_i \wedge q_i - \alpha_i D_i \wedge q_i$.

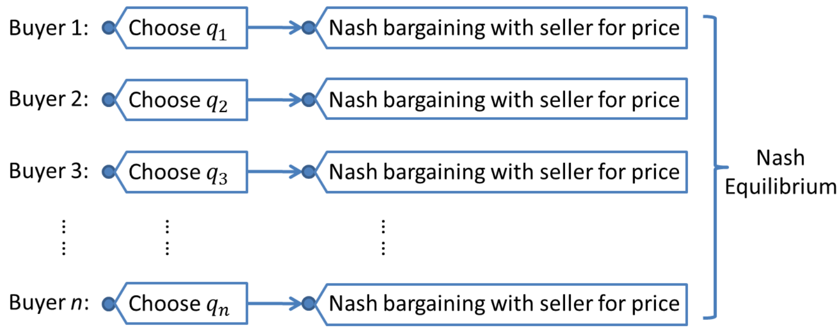
Externalities: Define S_t as the sum of purchase quantities across all buyers up to period $t = 1, 2$. Hence, we have $S_1 = \sum q_i$ and $S_2 = \sum (q_i + fq_i)$. The purchases result in two types of externalities. First, the seller's marginal production cost c is a decreasing convex function of the cumulative production quantity, which is an increasing function of the total purchase quantity; i.e., unit production cost is $c(S_t)$ in period t, for which $c' \leq 0$ and $c'' \geq 0$. Second, the value of product X for buyer i in period 1 is $v_i(S_1)$, for which $v' \geq 0$ and $v'' \leq 0$,[9] and the value in period 2 is $\rho \cdot v_i(S_2)$, where $\rho > 0$. The value is realized after a final product is sold, and it captures the value of product X in the end market net of the associated production and selling costs. Thus, leftover products will have zero value after period 2. In the base model, we assume $\rho = 1$, and time-dependent value with general ρ will be discussed in Section 7.1. For simplicity, we assume S_2 is large enough so that $c(S_2) \approx c(\infty) = c^*$ and $v_i(S_2) \approx v_i(\infty) = v_i^*$. Lastly, we assume that demand potential is independent of S_t. This is true when the network effect is restricted to the buyers,[10] and is also the convention in the literature (e.g., Bass 1969; Ho et al. 2002).

The Bargaining Game: The game proceeds as illustrated in Figure 5. At time zero, the seller chooses whether or not to use a fixed-price contract for the product; the type of contract will be applied to all the buyers (and a mixed contract choice will be discussed in Section 7.3). In

[9]This assumptions about $v_i(\cdot)$ is consistent with the model proposed by Katz and Shapiro (1985), the seminal work on general network effect.

[10]This is particularly true in the semiconductor industry, where the costs of software, hardware, and (manufacturing or testing) services that are compatible with a microchip are usually not the concerns of consumers.

Figure 6: Bargaining game in period 1.



period 1, buyer i decides her quantity q_i and enters a Nash bargaining (NB) with the seller for the price. We assume that the purchase quantity and the bargaining outcome is privy to each buyer (at least for a short period of time), so the multilateral bargaining process can be treated as a simultaneous move game (Cournot-Nash game) among all the buyers. In other words, the seller bargains simultaneously with all buyers who take other buyers' decisions and bargaining results into consideration. This is commonly assumed for bargaining with externalities (e.g., Horn and Wolinsky 1988). However, this game structure is not compatible with informational externality, which typically entails sequential moves. Thus, in our model, the externality with $v_i(\cdot)$ is due to the network effect only.

Let w_i' and w_i'' be the transaction prices for buyer i obtained through Nash bargainings in periods 1 and 2, respectively. If a fixed-price contract is used, then $w_i' = w_i''$; if the price is renegotiable, then w_i'' will be determined by another round of Nash bargaining for each buyer i. Since externalities no longer exist in period 2, buyers do not consider others in period-2 bargaining. The bargaining game in period 1 is illustrated in Figure 6.

Let β_i be the relative bargaining power of buyer $i \in N$ when bargaining with the seller. The *generalized Nash bargaining* model predicts that, if firm i's payoff and outside option for the focal transaction are $V_i(w)$ and θ_i given transaction price w, then the bargaining outcome is a price w^* that maximizes $(V_i(w) - \theta_i)^{\beta_i} \cdot (V_0(w) - \theta_0)^{1-\beta_i}$. In particular, if $V_i(w) - \theta_i + V_0(w) - \theta_0$ is independent of w, then w^* splits the fixed pie between the buyer and the seller in proportion to their respective bargaining powers. In addition, if a renegotiable-price contract is used and the bargaining breaks down in period 2, the buyer has to acquire a substitutable product of value

v_o from the outside market at cost c_o (including the switching cost such as reconfiguration of production line). For ease of exposition, let $\delta_o := v_o - c_o$, which is a measure for the strength of competition from alternative technologies or products.

Payoff Functions: Based on the assumptions laid out so far, buyer i's *ex-post* payoff can thus be formulated as

$$\begin{aligned} u_i =& v_i\left(S_1\right) \cdot s_{i1} - w_i' \cdot q_i + \rho \cdot v_i^* \cdot s_{i2} - w_i'' \cdot f q_i \\ =& \left(v_i\left(S_1\right) - w_i'\right) q_i - \left[q_i - \alpha_i D_i\right]^+ v_i\left(S_1\right) + \\ & \left(D_i \wedge q_i - \left(\alpha_i D_i\right) \wedge q_i\right) \rho v_i^* + \left(\rho v_i^* - w_i''\right) f q_i. \end{aligned} \tag{4}$$

In the second expression of u_i, the first three components are the payoff generated by the first purchase and the last component is the payoff generated by the second purchase. Given the set of contracts $\mathscr{C} := \{\mathscr{C}_i := (q_i, w_i', w_i'') : i \in N\}$, the seller's *ex-post* payoff can be formulated as

$$u_0 = \sum_{i\in N}\left(w_i' - c\left(S_1\right)\right) q_i + \sum_{i\in N}\left(w_i'' - c^*\right) f q_i, \tag{5}$$

which is the sum of total profits in period 1 and period 2. Let $U_i := \mathbf{E}\left[u_i|\mathscr{C}\right]$ denote firm i's ($i \in \{0\} \cup N$) expected payoff at time 0 given $\mathscr{C}$. Note that for buyer i, U_i is not only affected by her own quantity decision q_i but by also other buyers' decisions $q_{-i} := (q_1, \ldots, q_{i-1}, q_{i+1}, \ldots, q_n)$. To pin down the optimal quantity decisions, we focus on a pure strategy Nash equilibrium among the buyers in this paper.

4 Model Analysis

4.1 Centralized System (CS)

If firms are centralized, then the system payoff is $u_{CS} = u_0 + \sum_{i\in N} u_i$. Note that in our model the contract that generates a higher system payoff also brings a higher payoff for the seller. This is because the buyers and the seller always share the net system payoff proportionally to their bargaining power, given that their outside options are independent of the contract choice and they are risk-neutral. Hence, in this paper we consider a seller that aims to maximize the system payoff, and the payoff in a centralized system can serve as a benchmark for her to make the contract choice.

In a centralized system, bargaining is not necessary and the firms optimize their total expected payoff $U_{CS} = \mathbf{E}(u_{CS}(q))$ over $q := (q_1, \ldots, q_n)$. To simplify our notation, we introduce:

$$\begin{aligned}
\Delta_i(q_i|q_{-i}) :=& C_i^u(q_i|q_{-i}) - C_i^o(q_i|q_{-i}); \qquad (6)\\
C_i^u(q_i|q_{-i}) :=& v_i(S_1)\cdot\left[1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right] + \\
& c^*\cdot\left[b\left(1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right) + F_i\left(\frac{q_i}{\alpha_i}\right) - F_i(q_i)\right];\\
C_i^o(q_i|q_{-i}) :=& c(S_1) + b\rho v_i^*\cdot\left[1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right].
\end{aligned}$$

We call $\Delta_i(q_i|q_{-i})$ the *net mismatch cost*, and it is the marginal impact of q_i on the system payoff when its impact on the externalities is ignored. C_i^u and C_i^o are the expected underage and overage costs for buying one additional unit, respectively. The details for the underage and overage costs in different scenarios are illustrated in Table 3. After careful algebraic operations on $\partial U_{CS}/\partial q_i$, we get the result in Proposition 1.

Proposition 1. *In a centralized system, the incentive for adoption in period 1 for any buyer* $i \in N$ *is composed of three parts: the net mismatch cost* $\Delta_i(q_i|q_{-i})$*, the seller-based externality* $-c(S_1)' \cdot \sum q_j$*, and the buyer-based externality* $\sum v_j(S_1)' \cdot \mathbf{E}[q_j \wedge \alpha D_j]$*. In particular,*

$$\frac{\partial U_{CS}}{\partial q_i} = \Delta_i(q_i|q_{-i}) - c(S_1)' \cdot \sum_{j\in N} q_j + \sum_{j\in N} v_j(S_1)' \cdot \mathbf{E}[q_j \wedge \alpha_i D_j]. \qquad (7)$$

Several observations can be obtained from (7). Particularly, we are interested in whether $S_1 = 0$

Table 3: System-Wide Underage and Overage Cost for Producing One More Unit in Period 1

Demand	Period 1		Period 2	
Scenarios	Underage	Overage	Underage	Overage
$D_i \le q_i$	0	$c(S_1)$	0	0
$q_i < D_i \le \frac{q_i}{\alpha_i}$	0	$c(S_1)$	c^*	0
$\alpha_i D_i > q_i$; Exit	$v_i(S_1)$	$c(S_1)$	0	0
$\alpha_i D_i > q_i$; Wait	$v_i(S_1)$	$c(S_1)$	c^*	ρv_i^*

(called *adoption inertia*; see Jing 2011) or $S_1 > 0$ is obtained in the equilibrium. First, if $c(S_1)' = v_i(S_1)' = 0$, we have $\Delta_i(S_1 = 0) = (1 - b\rho)v_i^* - (1 - b)c^* \geq 0$ (assuming $v_i^* > c^*$). Hence, when externalities do not exist, it is always optimal for the system to purchase in the first period, and thus $S_1 > 0$ is obtained. However, if externalities do exist (i.e., $c(0)' < 0$ or $v_i(0)' > 0$ or both), the outcome is not obvious. If $b = 1$, then $\Delta_i(S_1 = 0) < 0$; if $b = 0$, then $\Delta_i(S_1 = 0) > 0$. Therefore, externalities and demand "backlogability" (or customer patience) play major roles. Since this is also true for the decentralized case, we have Corollary 1 below.

Corollary 1. *If externalities do not exist or end customers have zero patience, adoption inertia can never be obtained in equilibrium; if externalities do exist and end customers are perfectly patient, then adoption inertia can be obtained.*

4.2 Fixed-Price Contract

Now we look at the situation wherein fixed-price (FXP) contracts are used with all buyers. With an FXP contract, there is no more price bargaining after period 1, so we use $w_i := w_i' = w_i''$ to denote the price paid by buyer i. Since the bargaining outcome will determine each firm's payoffs in both periods, the total expected payoff U_i will be the target under negotiation. Thus, for buyer i, the Nash bargaining price $w_i^* = \arg\max_{w_i} (U_i - \theta_i)^{\beta_i} \cdot (U_0 - \theta_{0,i})^{1-\beta_i}$ given q_i and $\mathscr{C}_{-i}$. Assume θ_i is constant for all $i \in N$. Note that θ_i represents the highest payoff buyer i could achieve through other ways than buying from seller 0 in both periods at price w_i^*. Hence, w_i^* will guarantee that buyer i won't switch to other sellers in period 2 once the agreement on w_i^* is reached; in other words, θ_i represents the payoff from the outside market and is a fixed value, which is only a function of the type of buyer i. On the other hand, the seller will have business with other buyers in case of breakdown with buyer i, so his outside payoff when bargaining with buyer i is

$$\theta_{0,i}(\mathscr{C}_{-i}) = \sum_{j \neq i} \left(w_j - c\left(\sum_{j \neq i} q_j \right) \right) \cdot q_j + \sum_{j \neq i} (w_j - c^*) \cdot \mathbf{E}[f q_j]. \tag{8}$$

Next, it is important to observe from (4) and (5) that the sum $U_i + U_0$ is independent of w_i. As a result, the Nash bargaining price w_i^* leads to

$$U_i(q_i, \mathscr{C}_{-i}) = \theta_i + \beta_i [U_i(q_i, \mathscr{C}_{-i}) - \theta_i + U_0(q_i, \mathscr{C}_{-i}) - \theta_{0,i}(\mathscr{C}_{-i})], \tag{9}$$

for any q_i and $\mathscr{C}_{-i}$. Now with (9), we can optimize q_i for buyer i without knowing the explicit functional form of $w_i^*(q_i, \mathscr{C}_{-i})$ and have the following result.

Proposition 2. *With FXP contracts, the incentive for adoption in period 1 for any buyer $i \in N$ is weaker than in a centralized system. In particular,*

$$\frac{\partial U_i(q_i, \mathscr{C}_{-i})}{\partial q_i} \cdot \frac{1}{\beta_i} = \Delta_i(q_i|q_{-i}) - c(S_1)' \cdot \sum q_j + v_i(S_1)' \cdot \mathbf{E}[q_i \wedge \alpha_i D_i]. \tag{10}$$

The right-hand side of (10) looks very similar to (7). The only difference is that the buyer-based externality is reduced under an FXP (i.e., from $v_i(S_1)' \cdot \sum_j \mathbf{E}[q_j \wedge \alpha_i D_j]$ to $v_i(S_1)' \cdot \mathbf{E}[q_i \wedge \alpha_i D_i]$) so the buyer has less incentive to purchase in period 1. The intuition is that the seller and buyer i would not benefit from the gain (the increase of product valuation) of other buyers generated by a larger q_i, given the fixed-price contracts with all other buyers. Although the overall incentive—i.e., the first order derivative—is scaled down everywhere by factor β_i with FXP contracts, it has no impact on the optimal q_i.

4.3 Renegotiable-Price Contract

With renegotiable-price (RNP) contracts, buyers bargain for the price in both periods. We will refer to this scenario as "RNP." Since it is not necessary that buyers buy from the seller in the second period, the bargaining in the first period just focuses on the impact of the first-period purchase. Now we proceed backwards to analyze the two-period bargaining process.

Given the quantity q_i in period 1 and the assumption that D_i is known in period 2, we know that buyer i's purchase quantity in period 2 is $fq_i = [D_i - q_i]^+ - (1-b) \cdot [\alpha_i D_i - q_i]^+$. If she buys from the seller, buyer i can obtain payoff $(v_i^* - w_i'') \cdot fq_i$; otherwise, her outside payoff is $\delta_o \cdot fq_i$. For the seller, the payoff obtained with buyer i is $(w_i'' - c^*) \cdot fq_i$, and we assume that the outside payoff for him is zero given $\mathscr{C}_{-i}$. Hence, the generated pie is $(v_i^* - w_i'' - \delta_o) \cdot fq_i + (w_i'' - c^*) \cdot fq_i = (v_i^* - c^* - \delta_o) \cdot fq_i$, which is independent of w_i'', and thus the Nash bargaining price w_i'' splits the pie in proportion to their respective bargaining powers. As a result, we have $w_i'' = \beta_i c^* + (1 - \beta_i) \cdot (v_i^* - \delta_o)$.

We then look at the first-period bargaining problem. In case of a breakdown, the outside payoff of buyer i is θ_i^1, which is a function of her type and is fixed. Given others' quantities q_{-i}, if buyer i purchases q_i units, she obtains value $v_i(S_1) \cdot s_{i1} + v_i^* \cdot \min\{d_{i2}, q_i - s_{i1}\}$ with cost $w_i' \cdot q_i$. Let $U_{i,t}$ denote firm i's expected payoff that is generated by the period-t transaction. We already know $U_{i,2}(q_i)$. If we know $w_i'(q_i, \mathscr{C}_{-i})$, we then have $U_{i,1}(q_i, \mathscr{C}_{-i}) = v_i(S_1) \cdot \mathbf{E} s_{i1} + v_i^* \cdot \mathbf{E} \min\{d_{i2}, q_i - s_{i1}\} - w_i' \cdot q_i$ for $i \in N$. For the seller, we have $U_{0,1}(\mathscr{C}) = \sum_i (w_i' - c(S_1)) \cdot q_i$ and $\theta_{0,i}^1(\mathscr{C}_{-i}) = \sum_{j \neq i} \left(w_j' - c\left(\sum_{j \neq i} q_j\right)\right) \cdot q_j$. Thus, we can see that $U_{i,1}(q_i, \mathscr{C}_{-i}) - \theta_i^1 + U_{0,1}(\mathscr{C}) - \theta_{0,i}^1(\mathscr{C}_{-i})$, the size of the generated pie for the seller and buyer i in period 1, is also irrelevant to w_i'. As a result, the NB leads to

$$U_{i,1}(q_i, \mathscr{C}_{-i}) = \theta_i^1 + \beta_i \left[U_{i,1}(q_i, \mathscr{C}_{-i}) - \theta_i^1 + U_{0,1}(\mathscr{C}) - \theta_{0,i}^1(\mathscr{C}_{-i})\right] \tag{11}$$

for any q_i and $\mathscr{C}_{-i}$. Buyer i then decides on q_i based on its impact on the expected total payoff over the two periods; i.e., q_i should maximize $U_{i,1}(q_i, \mathscr{C}_{-i}) + U_{i,2}(q_i)$. Now with (11), we can optimize q_i without knowing the explicit functional form of $w_i'(q_i, \mathscr{C}_{-i})$ and have the following result.

Proposition 3. *With RNP contracts, the incentive for adoption in period 1 for any buyer $i \in N$ is weaker than with FXP contracts if $\delta_o > 0$; otherwise, the incentive is stronger than with FXP contracts. In particular,*

$$\begin{aligned}\frac{\partial U_i(q_i, \mathscr{C}_{-i})}{\partial q_i} \cdot \frac{1}{\beta_i} =& \Delta_i(q_i|q_{-i}) - c(S_1)' \cdot \sum q_j + v_i(S_1)' \cdot \mathbf{E}[q_i \wedge \alpha_i D_i] \\ &- \frac{1-\beta_i}{\beta_i} \cdot \delta_o \cdot \left[F_i\left(\frac{q_i}{\alpha_i}\right) - F_i(q_i) + b \cdot \left(1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right)\right].\end{aligned} \tag{12}$$

The difference between (10) and (12) is the second line in (12). It is an extra incentive generated by the possible change of price in the second period. Note that $F_i\left(\frac{q_i}{\alpha_i}\right) - F_i(q_i) + b \cdot \left(1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right) \geq 0$. Hence, the greater δ_o is, the less a buyer wants to buy in the first period, driven by a lower the second-period price. In contrast, a buyer wants to buy more in the first period, if δ_o is negative, which could be caused by a high switching cost or low valuation for the outside substitute. Note that δ_o could be a function of S_1 and we will discuss this situation in the extension.

Proposition 3 provides an important insight that complements our observation from the data. The data suggests that RNP contracts lead to significantly slower adoption than FXP contracts; however, our model suggests that this is not always the case. Therefore, the optimal contract choice is not obvious and depends on various factors as discussed in the next section.

5 Contract Comparison and Choice

When is a fixed-price contract better than a renegotiable-price contract? We discuss this question based on our analytic model. Denote as q^{CS} the optimal action profile in the centralized system. Denote as q^{FXP} and q^{RNP} the action profiles in the *pure strategy Nash equilibrium* (PSNE) for the two decentralized scenarios. The existence and uniqueness of the PSNEs may not be guaranteed. In the following, we characterize a sufficient condition for the existence of a PSNE in both decentralized scenarios. Define

$$\Lambda\left(q_i, Q_{-i}\right) := -2c'\left(q_i + Q_{-i}\right) - \left(q_i + Q_{-i}\right) \cdot c''\left(q_i + Q_{-i}\right) \qquad \text{and} \qquad (13)$$

$$\Gamma_i\left(q_i, Q_{-i}\right) := \bar{F}_i\left(\frac{q_i}{\alpha_i}\right) \cdot v_i'\left(q_i + Q_{-i}\right) + \mathbf{E}\left[q_i \wedge \alpha_i D_i\right] \cdot v_i''\left(q_i + Q_{-i}\right), \qquad (14)$$

where $Q_{-i} := \sum_{j \neq i} q_j$. It is easy to check that $\frac{\partial^2 U_i}{\partial q_i \partial Q_{-i}} \cdot \frac{1}{\beta_i} = \Lambda\left(q_i, Q_{-i}\right) + \Gamma_i\left(q_i, Q_{-i}\right)$ for any $i \in N$ in both decentralized scenarios. Thus, we have the following result.

Theorem 1. *If $\Lambda + \Gamma_i \geq 0$ for $\forall i \in N$, then a PSNE exists in both decentralized scenarios.*

The proof of Theorem 1 uses the property of a *supermodular game*. The condition is in general easy to be satisfied. Note that $c'(0) \leq 0$ and $v_i'(0) \geq 0$. First, let's focus on Λ, the component related to cost externality. The condition that $\Lambda \geq 0$ is simply that the learning effect satisfies $x \cdot c''(x) + 2c'(x) \leq 0$ for any $x \geq 0$. Without loss of generality, if we assume that $c(x) = c^* + \frac{A_2}{x + A_1}$, where $A_1, A_2 > 0$, then it is easy to check that $x \cdot c''(x) + 2c'(x) = -\frac{2A_1 A_2}{(x+A_1)^3} < 0$ for any $x \geq 0$. Second, for Γ_i, we can have a similar result if we assume a similar functional form for v_i and if $S_1 \cdot \bar{F}_i\left(\frac{q_i}{\alpha_i}\right) \geq 2 \cdot \mathbf{E}\left[q_i \wedge \alpha_i D_i\right]$, which is true if buyer i does not take a major share of the demand. Lastly, the condition holds if $\Lambda \geq |\Gamma_i|$, which indicates that the learning curve effect dominates. If $\frac{\partial^2 U_i}{\partial q_i \partial Q_{-i}} \geq 0$ holds for $\forall i \in N$, then it is a supermodular game. A PSNE exists for any supermodular game.

Now we assume the condition $\Lambda + \Gamma_i \geq 0$ for $\forall i \in N$ is satisfied. Then as a seller aiming to maximize the system payoff, how does one choose between an FXP and an RNP contracts? For simplicity, we assume the system payoff is at least quasi-concave in q. Given this assumption, *the scenario in which the action profile is "closer" to the centralized one is the better one for the system.* By comparing (7), (10), and (12), we get the following results.

5.1 Strength of Seller Competition

Recall that δ_o, the marginal payoff of the alternative product from the outside market in period 2, is a measure for the strength of competition from alternative technologies or products. It is an important factor that determines the difference between an FXP and an RNP in terms of early-adoption incentive. Given that it is a supermodular game, we can show that a stronger incentive for every buyer always leads to faster adopton for every buyer, making q^{CS}, q^{FXP}, and q^{RNP} comparable. To proceed, note that for vectors $\hat{q}$ and $\tilde{q}$, we say $\hat{q} < \tilde{q}$ if and only if $\hat{q}_i < \tilde{q}_i$ for every i. A similar definition applies to "$>$", "$\leq$", and "$\geq$" when used for vectors.

Proposition 4. *If q^{CS}, q^{FXP}, and q^{RNP} are unique, then (i) $q^{FXP} \leq q^{CS}$; (ii) if $\delta_o > 0$, then $q^{RNP} \leq q^{FXP}$; (iii) if $\delta_o < 0$, then $q^{RNP} \geq q^{FXP}$; (iv) and if $\delta_o = 0$, then $q^{RNP} = q^{FXP}$.*

Now we can compare the system payoff in each situation given different δ_o. For example, an FXP is better than an RNP if $q^{RNP} < q^{FXP} \leq q^{CS}$; this is the case if $\delta_o > 0$ (i.e., it is profitable to acquire a substitute in the outside market in period 2). However, the caution is that even in the opposite situation—i.e., $\delta_o < 0$—an RNP contract may not be better. For instance, when $\delta_o < 0$, we may have $q^{FXP} = q^{CS} < q^{RNP}$, which means an FXP contract is better. In other words, *faster product adoption may not always benefit the seller as well as the buyers.* In sum, an RNP contract is better than an FXP contract only when $\delta_o < 0$, but not too low.

5.2 Buyer Bargaining Power

If, in certain cases, the difference between FXP and RNP contracts is small—i.e., the two types of contract lead to similar results—then we need not spend too much time making a choice. Proposition 5 tells us that the absolute difference between q^{FXP} and q^{RNP} is decreasing in the bargaining power of every buyer. Hence, a wise contract choice is worthwhile only when buyers are not powerful. The intuition behind this finding is that when buyers are powerful, they can bargain to get a low enough price anyway and thus tactical decisions such as the intertemporal distribution of their purchase quantity does not have much impact.

Proposition 5. $\left\| q^{FXP} - q^{RNP} \right\|$ *is decreasing in β_i for any $i \in N$.*

As buyers become weaker and β_i gets closer to zero, $\left\| q^{FXP} - q^{RNP} \right\|$ increases even faster (due to the $\frac{1-\beta_i}{\beta_i}$ factor in (12)). When β_i becomes small enough so that we have either $q^{RNP} \ll q^{FXP}$

or $q^{RNP} \gg q^{FXP}$, then it is very likely that that $\left\|q^{CS} - q^{RNP}\right\| > \left\|q^{CS} - q^{FXP}\right\|$ and an RNP contract is less efficient than an FXP contract. Therefore, as β_i decreases for any $i \in N$, it becomes more and more likely that an FXP is the optimal choice. This is actually not intuitive, because as the seller becomes more and more powerful, he has more incentive to renegotiate and raise the price in period 2. If an RNP contract is used, however, the anticipated price increase would drive weak buyers to buy more in the first period, at the cost of supply-demand mismatch.

5.3 Size of Buyer Group

Another interesting factor is n, the size of the buyer group, which is essentially the scale of the "network." To simplify the analysis and to focus on the intuition, we assume for this subsection that the buyers are homogeneous. Let $Z_{FPX}(q) := \frac{1}{\beta} \cdot \frac{\partial U_{FXP}(q)}{\partial q} - \frac{\partial U_{CS}(q)}{\partial q}$ and $Z_{RNP}(q) := \frac{1}{\beta} \cdot \frac{\partial U_{RNP}(q)}{\partial q} - \frac{\partial U_{CS}(q)}{\partial q}$, where $U_{FXP}(q)$ and $U_{RNP}(q)$ represent the expected payoffs of a buyer with FXP and RNP contracts, respectively. Z_{FPX} or Z_{RNP} measures the difference between a decentralized system and the centralized one in terms of incentive to buy in period 1.

We can obtain that $\frac{\partial}{\partial n} Z_{FPX}(q) = \frac{\partial}{\partial n} Z_{RNP}(q) = -\mathbf{E}\left[q \wedge \alpha_i D\right] \cdot \left[v'(nq) + (n-1) \cdot q \cdot v''(nq)\right]$. Given n is large and $v(x) = v^* - e^{-x+A}$ or $v^* - \frac{1}{x+A}$, we have $v'(nq) + (n-1) \cdot q \cdot v''(nq) < 0$. Thus,

$$\frac{1}{\beta} \cdot \frac{\partial^2 U_{FXP}(q)}{\partial q \partial n} = \frac{1}{\beta} \cdot \frac{\partial^2 U_{RNP}(q)}{\partial q \partial n} > \frac{\partial^2 U_{CS}(q)}{\partial q \partial n},$$

which means that, as n increases, the changes to q^{FXP} and q^{RNP} are more positive than changes to q^{CS}. We know that q^{FXP} is bounded from above by q^{CS}, but q^{RNP} is not. Hence, as the size of the buyer group increases, q^{FXP} will approach q^{CS} but the chance of an RNP contract being the optimal choice decreases. (Note that the RNP contract is optimal only when $q^{RNP} > q^{FXP}$ but q^{RNP} is not too high.) The intuition behind this finding is that v is close to its limit in period 1 when n is large, so the extra incentive from an increase of v—which is the main difference between an FXP and a CS—is small.

5.4 Strengths of Externalities

Similarly, we assume for this subsection that the buyers are homogeneous. We have two types of externalities in our model, and the strengths of the externalities are captured by $c'(\cdot)$ and $v'(\cdot)$. If we take $c'(nq)$ and $v'(nq)$ as two variables, then we have

$$\frac{\partial Z_{FXP}(q)}{\partial c'(nq)} = \frac{\partial Z_{RNP}(q)}{\partial c'(nq)} = 0, \text{ and}$$
$$\frac{\partial Z_{FXP}(q)}{\partial v'(nq)} = \frac{\partial Z_{RNP}(q)}{\partial v'(nq)} = -(n-1) \cdot \mathbf{E}\left[q \wedge \alpha_i D\right] < 0.$$

Therefore, we have the following two observations. First, the strength of seller-based externality will have the same impact in all three cases, and we cannot tell how the optimal contract choice is affected. Second, as the strength of buyer-based externality $v'(\cdot)$ increases, the changes to q^{FXP} and q^{RNP} are more negative than changes to q^{CS}; i.e., the sizes of q^{FXP} and q^{RNP} relative to q^{CS} decrease. Given that the RNP is better than the FXP only if $q^{RNP} > q^{FXP}$, this finding means that the chance of the RNP contract being the optimal choice increases with the strength of buyer-based externality. The reason is that the increase of $v'(\cdot)$ amplifies the extra incentive from an increase of v, which is the main difference between an FXP and a CS.

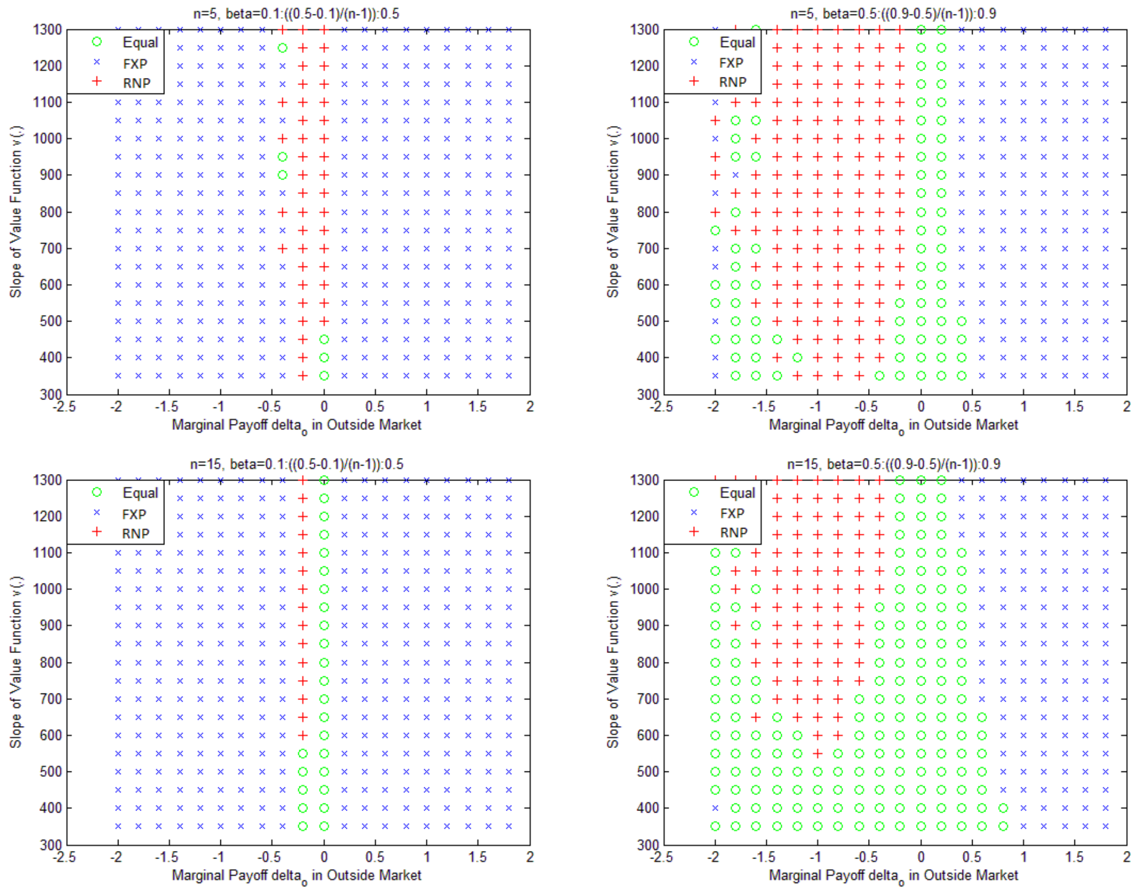
5.5 Computational Study

In this subsection, we generate numerical examples to explore the optimal contract choice for the system. We use $c(x) = c_* + \frac{A_2}{x+A_1}$ and $v_i(x) = v_i^* - \frac{B_2}{x+B_1}$, and make them satisfy the condition in Theorem 1. In particular, we set $\alpha_i = 0.5, b = 0.8, c^* = 1, v_i^* = 6$, and let the demand follow uniform distribution. As shown in Figure 7, the optimal choice of contracting regime depends on (i) δ_o, buyers' marginal payoff in the outside-market, (ii) β_i, buyer bargaining power, (iii) n, the size of the buyer group, and (iv) B_2, the slope of value function $v_i(\cdot)$. The results are consistent with the previous discussions.

5.6 Discussions

Therefore, if we want to suggest a type of contract for a seller, we shall consider the four dimensions of market characteristics. Note that the marginal payoff δ_o in the outside market is an indirect measure of degree of competition from rivalries within the industry. The other three dimensions (i.e., $v_i'(\cdot)$, β, and n) describe the structure of the downstream market. Moreover, these four metrics also provide us with a framework to predict the contract choice in many difference supply chains or industries. Based on our model, we can make the following conjectures. Readers who have related

Figure 7: The optimal choice of contract structure.



Note: Each dot ("o", "×", or "+") represents a problem instance with the corresponding parameters. The optimal contract choice for an instance is indicated by the symbol.

datasets may be able to test them.

- We shall see more RNP contracts in markets where competition is more balanced; i.e., it is not too hard or too easy for buyers to purchase from an alternative source. For example, if a product is offered by both Intel and AMD, but AMD's price is much lower, then we expect FXPs to be used by both sellers.

- We shall see more FXPs in markets where buyers are less powerful. For example, if we compare the supply chain of Intel and that of AMD, we expect Intel to use more FXPs.

- We shall see less RNPs in supply chains where a cost-learning effect exists and the buyer group is larger. In other words, if a product is a niche product that is purchased only by a few customers, then it would be very likely that we would observe an RNP.

- We shall see more diversified choices in industries where the role of buyer-based externalities is more significant. For example, the choices of contracting regimes should be more consistent for more basic component products such as memories and hard discs.

6 Model Extensions

6.1 Time-Dependent Valuation or Cost

Sometimes buyers' valuation for the (component) product is a function of time, regardless of the externalities. This type of valuation occurs because the component product will become obsolete, or because the final product will be obsolete, or the use of the component should be complemented by another critical part, the cost of which is changing over time. We can model this relation by setting a general $\rho > 0$ for period-2 valuation. With such a modification to the model, the incentive for buyers to adopt the product is affected by this time factor. According to (6), (7), (10), and (12), it is easy to obtain that

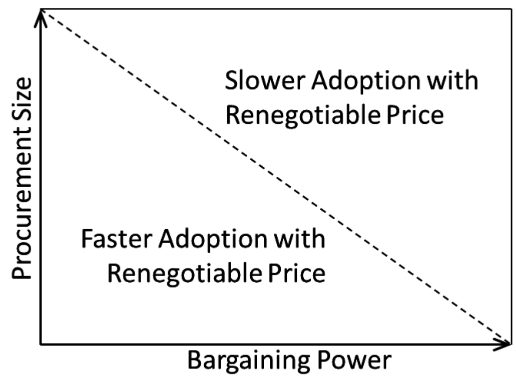
$$\frac{\partial^2 U_{CS}}{\partial q_i \partial \rho} = \frac{\partial^2 U_i^{FXP}}{\partial q_i \partial \rho} \cdot \frac{1}{\beta_i} = \frac{\partial^2 U_i^{RNP}}{\partial q_i \partial \rho} \cdot \frac{1}{\beta_i} = \frac{\partial \Delta_i}{\partial \rho} = -b \cdot \left[1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right]. \tag{15}$$

Hence, the incentive to adopt early decreases with ρ, which is intuitive. In particular, the sensitivity of buyer i's decision to ρ increases with b, α_i, and mean demand ($\int x dF_i(x)$). The flexibility for a buyer to manipulate the purchase intertemporally is captured by b and α_i. Since the impact of ρ is the same for both contracts, such a modification does not lead to qualitatively different results.

6.2 Lock-in Effect

The adoption of a product may not only affect the valuation and cost of this focal product, but also the cost and valuation for the substitute. This is the case when the purchase of the substitute generates externalities, or a switching cost (perhaps a lump sum cost) depends on the adoption of the focal product. In this subsection, we assume that, if the buyer turns to the outside market in period t, then the payoff is a function of q_{-i} in period $t = 1$ and is a function of q in period $t = 2$.

Figure 8: The impact of stronger externality associated with outside options.



First, it is easy to see that an FXP is not affected by such a modificaiton. Note that in period 1, buyer i's outside option θ_i represents the highest payoff she could achieve through other ways than buying from seller 0 in both periods. Hence, θ_i could be a function of q_{-i}, but not q_i. However, this won't affect the decision of q_i, because θ_i does not present in $\frac{\partial U_i^{FXP}}{\partial q_i}$.

On the other hand, when an RNP is used, the buyer's outside option in period 2, $\delta_o = v_o - c_o$, could be a function of q, and we have $U_{i,2} = [\beta_i \cdot (v_* - c_*) + (1 - \beta_i) \cdot \delta_o(q)] \cdot \mathbf{E}[fq_i]$. Hence,

$$\begin{aligned}\frac{\partial U_i^{RNP}}{\partial q_i} \cdot \frac{1}{\beta_i} &= \Delta_i(q_i|q_{-i}) - c(S_1)' \cdot \sum q_j + v_i(S_1)' \cdot \mathbf{E}[q_i \wedge \alpha_i D_i] \\ &- \frac{1-\beta_i}{\beta_i} \cdot \delta_o(q) \cdot \left[F_i\left(\frac{q_i}{\alpha_i}\right) - F_i(q_i) + b \cdot \left(1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right)\right] \\ &+ (1-\beta_i) \cdot \mathbf{E}[fq_i] \cdot \frac{\partial \delta_o(q)}{\partial q_i}. \end{aligned} \tag{16}$$

If we further assume that $\delta_o = a_0 - a_* \cdot S_1$, then

$$\frac{\partial^2 U_i^{RNP}}{\partial q_i \partial a_*} \cdot \frac{1}{1-\beta_i} = S_1 \cdot \left[F_i\left(\frac{q_i}{\alpha_i}\right) - F_i(q_i) + b \cdot \left(1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right)\right] - \beta_i \cdot \mathbf{E}[fq_i], \tag{17}$$

which indicates that the degree of externality may encourage or discourage early adoption. It is easy to see that for weak (i.e., β_i is small) and small-quantity (i.e., $\mathbf{E}[fq_i]$ is small) buyers, $\frac{\partial^2 U_i^{RNP}}{\partial q_i \partial a_*}$ is likely to be positive, and negative for strong and large-quantity buyers. Hence, with an RNP, *stronger externality associated with outside options may encourage weak and small buyers to adopt early and discourage large buyers to do so.* (See illustration in Figure 8.) The intuition is that (i)

weak buyers should buy more in period 1 and less in period 2 so that they can avoid paying high price in period 2 and (ii) for small-quantity buyers the increase of δ_o has relatively small impact on their payoffs. Last but not least, as the intensity (a_*) of externality on the outside option increases, δ_o may go from positive to negative, and thus the optimal contract choice may switch.

6.3 Mixed Contract Choices

In this subsection, we consider the case wherein the seller can use different types of contracts with different buyers. Propositions 2 and 3 suggest that the quantity decision of a buyer does not directly rely on the type of contract used for other buyers; instead, it only depends on the sum of other buyers' purchase quantities in period 1 (Q_{-i}). Hence, it is still a supermodular game if $\Lambda + \Gamma_i \geq 0$ for $\forall i \in N$. Given this assumption, we know from Theorem 1 that a PSNE exists no matter what contracts are used. The seller's problem can thus be formulated as follows:

$$\begin{aligned} \max \quad & U_{CS}(q) \\ s.t. \quad & q_i \in \left\{ q_i^{FXP}\left(q_{-i}\right), q_i^{RNP}\left(q_{-i}\right) \right\}, \quad \forall i \in N \end{aligned}$$

where $q_i^{FXP}\left(q_{-i}\right)$ solves Eq. (10) and $q_i^{RNP}\left(q_{-i}\right)$ solves Eq. (12). This is a highly non-linear problem with hardly any structural properties. Hence, it is an extremely difficult problem if n is large. However, n is usually a small number in reality, so it is possible to test 2^n possible solutions and find the optimal one. More importantly, mixed contract choices are not always desirable; in many cases, it is easy to tell that a dominant contracting regime exists. First, an FXP is a dominant choice if $q^{RNP} < q^{FXP}$, as suggested by Proposition 4. Second, an RNP is a dominant choice when $q^{FXP} \leq q^{RNP} \leq q^{CS}$. Lastly, mixed choices may be desirable only when $q^{FXP} < q^{CS}$ and there exists i such that $q_i^{RNP} > q_i^{CS}$.

7 Conclusions

In this paper, we study product-adoption process management in high-tech supply chains and the contract choice for sellers selling to business buyers. We consider a market in which demand is uncertain in the end market, is learned over time, and is independent of the product adoption. The adoption generates positive externalities among the buyers, and the price for a product is subject to negotiations. The task of the seller is to manage product adoption at a favorable pace that maximizes system payoff.

Given that intertemporal pricing schemes are not viable in this situation, we propose that the seller could consider choosing whether to allow the price with a buyer to be renegotiated in future purchases, or to sign a long-term, fixed-price contract with a buyer. Using a dataset supplied by a major global microchip vendor and an approach based on an instrumental variable, we observe a causal relation between price variability and buyer behavior. The causal relation suggests that contract design in terms of price flexibility is an effective lever for product-adoption process management. To understand how the price mechanism would affect buyer behavior in different situations, we build a simple dynamic game-theoretic model to explore the dynamics associated with different types of contracts and study how to make the contract choice for the seller.

Our model shows that the optimal choice of contract depends on (*i*) the source and degree of externality, (*ii*) the strength of sell-side competition, (*iii*) buyer's bargaining power, and (*iv*) the number of the buyers. First, our model indicates that a more diversified use of contracts in industries where the role of buyer-based externalities (i.e., network and informational externalities) is stronger. By contrast, the contract choices should be more consistent for more basic component products such as memories. When significant buyer-based externalities are present and switching is costly for buyers, a fixed-price contract is not efficient because the seller loses the flexibility to increase the price later. Second, it indicates that we should use fixed-price contracts less frequently where the market competition is more balanced (i.e., neither too hard nor too easy to buy from an alternative source). The intuition is that, when it is not too easy to find a substitute, buyers have no incentive to delay their purchases; when it is not too hard, buyers will not buy too much at early stage when demand is highly uncertain. Third, we should use more fixed-price contracts in markets where buyers are less powerful because weak buyers are very sensitive to price changes over time and tend to adopt the product too early or too late. Last but not least, in markets where a learning effect exists and the buyer group is larger, renegotiable-price contracts are less likely to outperform fixed-price contracts. In this case, the reason is because the price will go down significantly due to the learning effect and thus buyers do not have an incentive to buy early.

We then extend the model to incorporate time-dependent valuation, externality on outside options, and mixed contract choices. We find that time dependence does not change our results. Also, we find that stronger externality on outside options may encourage weak and small buyers to adopt early and discourage large buyers to do so; as the degree of externality on the outside option increases, the optimal contract choice may switch from a fixed-price to a renegotiable-price contract. Lastly, mixed contract choices are not always desirable, and in many cases it is easy to tell whether a dominant contracting regime exists. Admittedly, there are still limitations for our empirical and theoretical analyses. In particular, our data is from a single company and it may have limited statistical power. In addition, we assume that the positive externalities do not benefit end consumers directly and that demand potential is independent of adoption. Due to these limitations, our work may serve as a strategic guide of contract choice for the management of new product adoption in high-tech supply chains. Extending our model to incorporate these limitations could be a fruitful area for future research.

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Appendix

The Measure of Contract Type: Here we discuss why we do not choose the three alternative measures. (i) There are three problems with *the average duration of a price*. Firstly, the flexibility measured by the duration of a price is relative to the duration of the instance.[11] Even if we normalize the duration of price and divide it by the duration of instance, there is still a problem. Some instances have a fixed price most of the time, but they have a couple of single transactions where the price has jumped or dropped. Those exceptions only account for a negligible proportion of the duration of an instance but can greatly drag down the average duration of price. Lastly, an average duration of price cannot capture the extent of price changes that is allowed by a contract. (ii) In comparison, *the variance of price* is more robust to exceptional price deviations and can also capture the extent of price change. The price variance *ex ante* is an increasing function of the flexibility of contract. However, different products have different price levels, so the variance has to be normalized. (iii) *The coefficient of variation* (CV) *of price* is defined as the quotient of

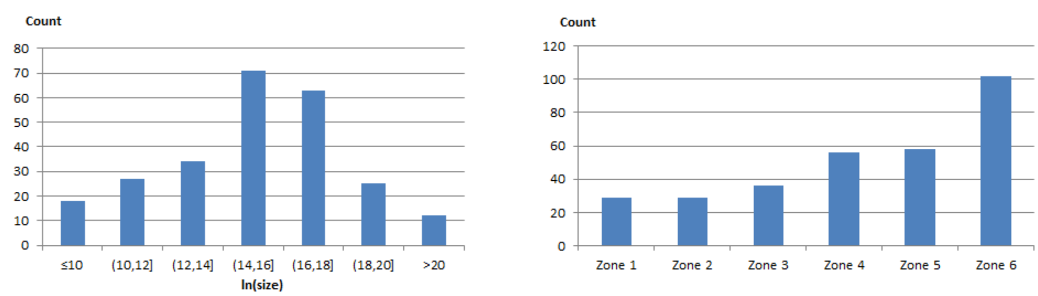
[11] For example, instance θ has average duration of price equal to 1 month and instance θ' has an average duration of price equal to 2 months; however, the duration of θ is only 1 month and the duration of θ' is 1 year. In this example, φ of θ' has higher flexibility.

Table 4: Test for Major Customers

Customer	ln($size$)	Instances	Coefficient	t Stat	P-value
#1	22.31	159	-0.0175	-0.85	0.4
#2	20.91	203	-0.4277***	-3.73	0.0002
#3	19.52	150	-0.0001	-0.0235	0.9813
#4	21.25	120	-0.0871**	-2.12	0.0357
#5	21.50	386	-0.0008*	-1.8865	0.0600
#6	20.22	161	-0.3643**	-2.0970	0.0376
#7	20.97	149	-0.6560***	-3.7604	0.0003
#8	20.25	146	-0.0804*	-1.9061	0.0586
#9	21.27	163	-0.2508*	-1.8144	0.0715
#10	20.44	214	-0.3522***	-2.7387	0.0067

Note: *p<0.1; **p<0.05; ***p<0.01.

Figure 9: Customer distributions on two characteristics.



standard deviation of price over the mean. Similar to the problem of price duration, the mean of price is sensitive to some exceptional price jumps or drops that typically occur at the end of the life cycle. In sum, the variance of price is better than the average duration of price; the CV of price is better than the variance of price; and the ACVP improves the CV of price. The ACVP is the best among all these measures.

Test of Buyer-Specific Common Causes: Here we show a contradiction if we suppose that hypothesis (I) is not true and that ε and ε' are buyer-specific factors. Ideally, we should test the correlation between the ACVP and TDPS for each individual buyer. However, for medium- to small-sized buyers, we do not have a large enough sample size. Hence, we first focus on the top ten

Table 5: Test for 10 Customer Groups

Group	ln($size$)	Coefficient	t Stat	P-value
#1	[8.57, 14.62]	0.0656	0.5972	0.5516
#2	[14.62, 16.12]	-0.5975***	-4.8786	0.0000
#3	[16.12, 17.27]	-0.4234**	-2.1792	0.0314
#4	[17.27, 17.64]	-0.5470***	-4.3592	0.0000
#5	[17.64, 18.28]	-0.8911***	-3.8355	0.0002
#6	[18.28, 18.79]	-0.6192***	-3.4272	0.0009
#7	[18.79, 19.32]	-0.5244***	-3.0807	0.0028
#8	[19.32, 19.38]	-0.0007	-0.3124	0.7554
#9	[19.38, 19.58]	-0.5719***	-3.3443	0.0011
#10	[19.58, 20.49]	-0.6373***	-4.9492	0.0000

Note: *p<0.1; **p<0.05; ***p<0.01.

major buyers that have close to or more than 150 instances recorded in our dataset. The results are summarized in Table 4. We see that for most (8/10) of these major buyers, the correlation between ACVP and TDPS is still significant with total quantity controlled, which is a strong evidence of these buyers responding strategically to the contract type.

To test the correlation for other buyers, we control the two buyer-specific characteristics: size and location. We believe that these two characteristics capture some inherent attributes that might lead to the correlation; otherwise, it is hard to imagine that customers would act differently due to some other factors even if they were offered the same contract.[12] As shown on the left in Figure 9, we get a distribution that is very close to normal if we plot the distribution of buyers according to the logrithmic function of their total purchasing values (i.e., $\ln(size)$). For location, there are 6 major geographic zones according to the data, and the buyer distribution across the zones is shown on the right in Figure 9. We then pick the zone that has the most customers, and equally divide buyers into 10 subgroups according to their sizes so that we have roughly 113 instances in each subgroup. The test results are summarized in Table 5. We see that for 8 out of the 10 buyer groups, the correlation between ACVP and TDPS is still significant with total quantity controlled,

[12] Buyers from different micromarkets might have different behaviors and contract practices, but buyers in the same micromarket tend to purchase similar products. Hence, a micromarket-related characteristic is almost equivalent to a product-specific characteristic. Moreover, we believe that the difference between new and old buyers is not a major concern, because there is no reason for a new buyer to behave differently from an old one in a consistent way regardless of the form of the contract.

which further supports our claim that buyers are responding to the contract type.

Proof of Lemma 1: First, fq_i cannot take values other than $\left[d_{i2} - [q_i - \alpha_i D_i]^+\right]^+$ given that D_i is known and the purchase price is positive. Suppose the following scenario. If buyer i reduces fq_i, she looses profit; if she increases fq_i, then her cost increases but revenue is unaffected. Hence, the second period purchase quantity should equal period-2 total demand, and thus

$$\begin{aligned} fq_i &= \left[b\left[\alpha_i D_i - q_i\right]^+ + (1-\alpha_i)D_i - [q_i - \alpha_i D_i]^+\right]^+ \\ &= \begin{cases} D_i - q_i - (1-b)\left(\alpha_i D_i - q_i\right) & \text{if } D_i > q_i/\alpha_i \\ D_i - q_i & \text{if } q_i < D_i \leq q_i/\alpha_i \\ 0 & \text{if } D_i \leq q_i \end{cases} \\ &= [D_i - q_i]^+ - (1-b)\left[\alpha_i D_i - q_i\right]^+ ; \\ s_{i2} - fq_i &= b\left[\alpha_i D_i - q_i\right]^+ + (1-\alpha_i)D_i - [D_i - q_i]^+ + (1-b)\left[\alpha_i D_i - q_i\right]^+ \\ &= D_i \wedge q_i - \alpha_i D_i \wedge q_i. \ \square \end{aligned}$$

Proof of Proposition 1:

$$U_{CS} = \sum_{i \in N} v_i\left(S_1\right) \cdot \mathbf{E}\left[q_i \wedge \alpha_i D_i\right] - c\left(S_1\right) \cdot S_1 + \sum_{i \in N} \rho \cdot v_i^* \cdot \mathbf{E}\left[s_{i2}\right] - c^* \cdot \sum_{i \in N} \mathbf{E}\left[fq_i\right]$$

It is easy to check that $v_i\left(S_1\right) \partial \mathbf{E}\left[q_i \wedge \alpha_i D_i\right] / \partial q_i - c\left(S_1\right) + \partial\left[\rho v_i^* \mathbf{E}\left[s_{i2}\right] - c^* \mathbf{E}\left[fq_i\right]\right] / \partial q_i = \Delta_i$, where Δ_i is defined in (6). Then Eq. (7) is obtained. $\square$

Proof of Proposition 2:

$$\begin{aligned} U_i\left(q_i, \mathscr{C}_{-i}\right) =& \theta_i + \beta_i\left[U_i\left(q_i, \mathscr{C}_{-i}\right) - \theta_i + U_0\left(q_i, \mathscr{C}_{-i}\right) - \theta_{0,i}\left(\mathscr{C}_{-i}\right)\right] \\ =& \theta_i + \beta_i\left[v_i\left(S_1\right) \cdot \mathbf{E}\left[q_i \wedge \alpha_i D_i\right] - c\left(S_1\right) \cdot S_1 + \right. \\ & \left. c\left(Q_{-i}\right) \cdot Q_{-i} + v_i^* \cdot \mathbf{E}\left[s_{i2}\right] - c^* \cdot \mathbf{E}\left[fq_i\right] - \theta_i\right]. \end{aligned}$$

Similarly, $v_i\left(S_1\right) \cdot \partial \mathbf{E}\left[q_i \wedge \alpha_i D_i\right] / \partial q_i - c\left(S_1\right) + \partial\left[v_i^* \cdot \mathbf{E}\left[s_{i2}\right] - c^* \cdot \mathbf{E}\left[fq_i\right]\right] / \partial q_i = \Delta_i$. Then Eq. (10) is obtained. $\square$

Proof of Proposition 3: Firstly, $U_{i,2}(q_i) = [\beta_i(v_i^* - c^*) + (1-\beta_i)\delta_o] \cdot \mathbf{E}[fq_i]$. Hence,

$$\begin{aligned}U_i(q_i, \mathscr{C}_{-i}) =& \theta_i^1 + \beta_i\left[U_{i,1}(q_i, \mathscr{C}_{-i}) - \theta_i^1 + U_{0,1}(\mathscr{C}) - \theta_{0,i}^1(\mathscr{C}_{-i})\right] + U_{i,2}(q_i) \\ =& \theta_i^1 + \beta_i\left[v_i(S_1) \cdot \mathbf{E}[q_i \wedge \alpha_i D_i] - c(S_1) \cdot S_1 + \right. \\ & \left. c(Q_{-i}) \cdot Q_{-i} + v_i^* \cdot \mathbf{E}[s_{i2}] - c^* \cdot \mathbf{E}[fq_i] - \theta_i^1\right] + \\ & (1-\beta_i) \cdot \delta_o \cdot \mathbf{E}[fq_i].\end{aligned}$$

We have $v_i(S_1) \cdot \partial \mathbf{E}[q_i \wedge \alpha_i D_i]/\partial q_i - c(S_1) + \partial[v_i^* \cdot \mathbf{E}[s_{i2}] - c_* \cdot \mathbf{E}[fq_i]]/\partial q_i = \Delta_i$. In addition, $\partial \mathbf{E}[fq_i]/\partial q_i = F_i(q_i) - F_i\left(\frac{q_i}{\alpha_i}\right) - b\left[1 - F_i\left(\frac{q_i}{\alpha_i}\right)\right]$. Then Eq. (12) is obtained. □

Proof of Theorem 1: If $\frac{\partial^2 U_i}{\partial q_i \partial Q_{-i}} = \beta_i(\Lambda + \Gamma_i) \geq 0$ for $\forall i \in N$, it is a supermodular game. A PSNE exists for any supermodular game. □

Proof of Proposition 4: (i) According to (7) and (10), $\frac{1}{\beta_i} \cdot \frac{\partial U_i^{FXP}}{\partial q_i}|_{q=q^{CS}} = \frac{\partial U_{CS}}{\partial q_i}|_{q=q^{CS}} - \sum_{j \neq i} v_i\left(\sum q_i^{CS}\right)' \cdot \mathbf{E}\left[q_j^{CS} \wedge \alpha_i D_j\right] \leq \frac{\partial U_{CS}}{\partial q_i}|_{q=q^{CS}}$ for $\forall i \in N$. Hence, it is not possible that $q^{FXP} \geq q^{CS}$. Given that it is a supermodular game, it must be that $q^{FXP} \leq q^{CS}$. (ii) According to (10) and (12), $\frac{\partial U_i^{RNP}}{\partial q_i}|_{q=q^{FXP}} = \frac{\partial U_i^{FXP}}{\partial q_i}|_{q=q^{FXP}} + (1-\beta_i) \cdot \delta_o \cdot \frac{\partial \mathbf{E}[fq_i]}{\partial q_i} \leq \frac{\partial U_i^{FXP}}{\partial q_i}|_{q=q^{FXP}}$ for $\forall i \in N$ if $\delta_o > 0$. Hence, $q^{RNP} \geq q^{FXP}$ is not possible; it must be that $q^{RNP} \leq q^{FXP}$. Similar arguments apply to (iii) and (iv). □

Proof of Proposition 5: First, suppose $\delta_o > 0$. According to Proposition 4, $q^{RNP} \leq q^{FXP}$ for any $0 < \beta < 1$. Because $\frac{\partial q_i^{FXP}}{\partial \beta_i} = 0$ and $\frac{\partial q_i^{RNP}}{\partial \beta_i} \geq 0$, we know $\left|q_i^{FXP} - q_i^{RNP}\right|$ is decreasing in β_i. Because it is a supermodular game, we have that $\left|q_j^{FXP} - q_j^{RNP}\right|$ is decreasing in β_i for all $j \neq i$. The result follows. □