The Bright Side of Price Volatility in Global Commodity Procurement

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Abstract: This paper studies two competing firms' choices between the contingent-price contract (CPC) and fixed-price contract (FPC) in global commodity procurement. The FPC price is determined when signing the contract, whereas the CPC price is pegged to an underlying index and remains open until the delivery date. Under both contracts, each firm determines its order quantity based on the updated belief about the market demand. The unrealized CPC price correlates with the market demand, allowing a firm to update its belief about the CPC price using demand information, thereby generating a price-learning effect. We find that, contrary to conventional wisdom, a larger price volatility could benefit the firms, and, under differentiated contracts, a firm might benefit from the improvement of forecast accuracy at its rival. We further show that the price-learning effect plays a critical role in the firms' contract choices. First, significant price volatility forces the firms to pursue the responsiveness of the CPC. Second, the firms may adopt differentiated contracts to enhance their responses to market changes and dampen competition, and a higher competition intensity more likely leads to contract differentiation. Third, the firms in a small market seek responsiveness and contract differentiation rather than cost efficiency. This study reveals the bright side of price volatility and takes a step toward understanding the effect of two-dimensional information updating.

Keywords: Global commodity procurement; contingent pricing; price volatility; information updating; correlation; competition

1. Introduction

The dramatic geographic separation of supply sources and consumption markets has made global commodity procurement a highly challenging business. For example, Australia and Brazil supply the majority of iron ore worldwide, whereas China, Japan, and South Korea, located in another part of the world, consume over 80% of the total global iron ore supply. Chile and Argentina are the biggest exporters of lithium carbonate in the world, whereas South Korea is the foremost lithium carbonate importer, followed by China and Japan. Global commodity procurement entails a complex and long trading process, including sourcing, contracting, financing and payment, ocean and land transport, and customs clearance. The total procurement lead time is typically in months. Consequently, uncertainties arise from both supply and demand sides and pose significant challenges to importers (e.g., traders who import to resell and manufacturers who import as production input). On the supply side, commodity price fluctuations hamper importers' efforts to control procurement costs. On the demand side, long procurement lead times and market demand uncertainties cause mismatches between procured quantities and market demands. In a competitive setting, importers lose sales and market shares when they underestimate market demands or have to sell at losses (i.e., market prices are lower than procurement costs) when demands are overestimated.

Importers generally need recurrent procurement for continuous production or sales, but this would incur significant transaction costs and operational uncertainties if they have to source and negotiate with suppliers for each order. Hence, it is a common practice for importers and suppliers to establish long-term contracts that specify the pricing, payment, and quality terms to cover a period of months or an even longer procurement horizon, during which multiple orders can be made without renegotiation (e.g., Vale 2013). In a long-term contract, the two parties reach an agreement on the total procurement quantity with a certain flexibility (e.g., ±20% within the agreed quantity) but the quantity of each order is not specified. The pricing scheme in the long-term contract is critical for the importer. The fixed-price contract (FPC), which defines a pre-determined price for the procurement horizon, is the traditional pricing mechanism. However, a significantly different pricing scheme, namely, the contingent-price contract (CPC), has become popular in recent decades.

Under a CPC, the procurement price of an order is pegged to a well-known price index or futures price of the commodity and remains open until the order is physically delivered.

The CPC and FPC are representative of the contracts commonly used in the trade of ores, metals, and agricultural products (e.g., Feng et al. 2013, Boyabatlı et al. 2011, and Li et al. 2018). It is well known that before 2009, global iron ore giants (i.e., BHP, Rio Tinto, and Vale) and Asian steelmakers engaged in multilateral negotiations to determine an annual fixed price for all procurement orders during the coming year. After 2009, the annual negotiated FPC was gradually replaced by the quarterly contract with a price pegged to the three-month average of the Platts Iron Ore Index (IODEX) (Chen et al. 2013, Vale 2013). For example, the contract price for the orders in the third quarter is determined in June based on the average IODEX of March, April, and May. The quarterly contract is just a variant of the annual FPC. Meanwhile, the global iron ore market also began to adopt the CPC, where the contract price is mostly linked to the IODEX at the time of the delivery of the order (Vale 2013). Currently, these two types of index-based pricing schemes are extensively used for contracts in the global iron ore market (Vale 2021).

The pros and cons of the CPC and FPC have been discussed extensively in the business press. It is clear that the FPC enables importers to lock in the procurement costs in advance and hence avoid the up-side risk of price volatility. By contrast, the CPC is risky because importers bet on the future movements of commodity prices. However, there are also different voices that the FPC is rigid because the fixed price cannot be adjusted based on the market situation at the time of delivery, whereas the CPC price, although volatile, provides a lever for importers to respond to demand changes (Bhattacharyya and Deepak 2012). The past decade has witnessed increasing price fluctuations for many commodities (see www.imf.org/commodities). Under such drastic price fluctuations, different contracts can lead to significantly different procurement costs. For instance, the IODEX in 2019 dropped from \$126 per ton in July to \$81 per ton in August. The rapid price fall coupled with the sluggish demand in China caused huge losses to the importers who procured under the FPC. Therefore, importers need to choose strategically between the CPC and FPC when their competitors also face the same challenge.

Accurate demand information is critical for importers to make the right order quantity decisions. Under the FPC, an importer determines the order quantity based on its belief about the market demand. However, an importer under the CPC faces uncertainties from both the market demand and procurement price, and the index underlying the price is typically correlated with the uncertain demand (see, e.g., Seifert et al. 2004, Kouvelis et al. 2013). For instance, China accounted for about 72% of worldwide iron ore imports in 2020. Hence, strong market demand for iron ore in China usually pushes the IODEX upward. Nowadays, abundant trading data and advanced data analytics technologies help importers understand the correlation between these uncertain variables. Thus, an importer's demand information can be used to update its belief not only on the market demand but also on the underlying index and hence the procurement price. With such two-dimensional (demand-side and cost-side) information updating, the ordering decision of an importer under the CPC can differ significantly from that under the FPC.

Commodity procurement has been an important topic in the operations management literature, and a number of researchers have investigated the risk-sharing mechanisms for the CPC in vertical supply chain settings (e.g., Li and Kouvelis 1999, Boyabatlı et al. 2011, Feng et al. 2013, Zhang et al. 2014, Goel and Tanrisever 2017, and Kouvelis et al. 2018). However, few papers have studied the effect of price volatility of the CPC in a horizontal competitive setting, and the driving force behind the popularity of the CPC in global commodity procurement is under-explored. Moreover, two-dimensional information updating, a critical factor affecting commodity procurement decisions, has received little attention in the literature on information acquisition. Therefore, this study aims to fill the above research gaps. In particular, we attempt to answer the following research questions: (1) How does the price volatility of the CPC affect two-dimensional information updating as well as the ordering decisions of competing importers? (2) Is price volatility always detrimental to importers as traditionally believed? (3) Under what market situations should an importer adopt the CPC or FPC? (4) What are the underlying reasons behind the popularity of the CPC despite its seemingly high risk?

We develop a game-theoretic model in which two firms procure a commodity offshore to resell in a local market (or to produce substitutable products for sale in a downstream market). We focus on the two key stages of the global commodity procurement process: the sourcing and ordering stages. In the sourcing stage, each firm signs a long-term sourcing contract with an offshore supplier, under which the pricing scheme is determined. That is, the firms play a *sourcing game* by making choices between the CPC and FPC. Then, in the ordering stage, the firms place orders in each subsequent period. Without loss of generality, we consider only one period where the firms engage in a *Cournot game*: They first determine their respective order quantities based on their latest information and then sell the commodity after the orders are physically delivered.

With the above model setting, we identify a *price-learning effect* arising from the use of the CPC: The correlation between the CPC price and market demand allows a firm to update its belief on the procurement price using demand information. Such an effect drives two interesting outcomes. First, significant price volatility compels a firm to focus more on aligning its order quantity with the perceived CPC price than on matching the order quantity with the updated demand. This alignment creates a greater value for the firm as the CPC price becomes more volatile, suggesting that higher price fluctuations are not always detrimental to importers. Conversely, the ordering decision based on financially hedged price volatility is not always beneficial because it may limit the firms' responsiveness to market changes. This finding also offers suggestions on how to utilize price volatilities, e.g., selecting a suitable underlying index in CPC designs. Second, the improvement of a firm's forecast accuracy may also benefit its rival under differentiated contracts. The reason is that the price-learning effect allows the firms to adjust their quantities oppositely in response to their private information; and accordingly, the improvement of one firm's forecast accuracy can enhance the responsiveness of both firms and hence their profits. This finding provides a new explanation for adopting differentiated contracts and implies that competing firms can use contract differentiation to avoid over-investment in costly information acquisition. We emphasize that the price-learning effect originates from the interaction between price volatility and information updating. This effect no longer exists when the CPC price and market demand are independent.

We further explore the contract choices of the competing firms under different procurement cost structures. We find that without the price-learning effect, the firms always pursue the cost efficiency of either the CPC or FPC. With the price-learning effect, however, the firms' contract choices are significantly different. First, when the expected procurement costs of the CPC and FPC are equal, the firms seek the stronger responsiveness of the CPC in the presence of significant price volatility, which compels the firms to adjust the quantities mainly based on their perceived CPC prices rather than relying on updated demand. Second, asymmetric sourcing equilibria may arise even if the firms are ex-ante symmetric. This is because contract differentiation allows the firms to adjust their order quantities in opposite directions and thus improves their responsiveness and dampens competition. In addition, a higher competition intensity drives the firms more toward contract differentiation. Third, the firms face a trade-off between cost efficiency and responsiveness when one of the contracts offers a cost advantage. The firms always pursue cost efficiency if the market size is sufficiently large. By contrast, the firms in a small market prefer responsiveness and contract differentiation; in this case, a superior forecaster should purely pursue stronger responsiveness but an inferior forecaster also needs to consider the value of contract differentiation. We therefore conclude that utilizing the price-learning effect, dampening competition, and seeking cost efficiency are three factors that contribute to the prevalence of the CPC.

This paper contributes to the literature by revealing the bright side of price volatility and illustrating the respective suitability of the CPC and FPC for global commodity procurement in a horizontal competitive setting. It also deepens our understanding of the effect of information updating by considering a two-dimensional rather than one-dimensional setting.

The rest of this paper is organized as follows. Section 2 reviews the literature, and Section 3 describes the model. Section 4 analyzes Cournot subgames, and Section 5 examines the effect of price volatility. The firms' contract choices are explored in Section 6. Finally, the paper concludes in Section 7. Extensions and proofs are provided in the Appendix.

2. Literature Review

The literature on commodity procurement is extensive, yet only a small but crucial branch touches on the CPC. Li and Kouvelis (1999) study how a downstream firm shares the price risk with its supplier through a market-based adjustable contract. Boyabatlı et al. (2011) explore a beef processor's production decision by considering the interaction of spot purchasing and window contract procurement in which the contract price is based on a spot price. By using a Nash bargaining approach, Feng et al. (2013) design a market-based adjustable contract and provide suggestions on contract choices between the adjustable contract and the FPC. Zhang et al. (2014) compare five types of contracts (including the CPC and FPC) and find that the CPC may be optimal for the buyer when the supplier is risk neutral. Goel and Tanrisever (2017) propose a CPC where the price is a weighted function of futures and spot prices to hedge against price volatilities. Kouvelis et al. (2018) design contracts to coordinate a supply chain with uncertainties from both demand and input sides and find that the transfer price and default penalty must be pegged to the price of the commodity that the members purchase. By considering the risk aversion of supply chain members, Li et al. (2018) show that the CPC outperforms the FPC when the firm's postponed processing cost is lower than a threshold. Two factors distinguish our work from the aforementioned studies. First, the above studies consider vertical supply chains and focus on the risk-sharing mechanism, whereas our paper analyzes the responsiveness of the CPC in a horizontal competitive setting. Second, two-dimensional information updating plays a critical role in determining the firms' commodity procurement decisions, which is absent from the aforementioned studies.

This paper is also related to the literature on information acquisition and sharing involved in horizontal competition. Early studies in the economics literature focus on the incentive and impact of information sharing among competing firms (see, e.g., Vives 1984, Li 1985, and Shapiro 1986). A group of papers explore vertical information sharing under different supply chain structures, where horizontal competition occurs at either the downstream or upstream of the supply chains (e.g., Li 2002, Li and Zhang 2008, Gal-Or et al. 2008, Ha and Tong 2008, Anand and Goyal 2009, Shin and Tunca 2010, Ha et al. 2011, Jiang and Hao 2016, Shang et al. 2016, Ha et al. 2017, and

Liu et al. 2021). There are also several studies on operations management that involve various informational issues. Wu and Zhang (2014) analyze competing firms' sourcing strategies, in which responsive sourcing enables a firm to acquire more accurate demand information than efficient sourcing. Li et al. (2014) find that, under asymmetric information, supplier encroachment may amplify double marginalization. Bimpikis et al. (2019) explore an information provider's selling strategy to customers who compete in a product market. Chen and Tang (2015), Tang et al. (2015), Liao and Chen (2017), He et al. (2018), Liao et al. (2019), and Zhou et al. (2021) study the value of various information policies in agricultural settings. Our paper differs from the aforementioned studies in that competing firms acquire private demand signals to update their beliefs not only on the market demand but also on the procurement price. We contribute to the literature by revealing how different contracts affect information updating in global commodity procurement. To our knowledge, this study is the first in the literature aiming at understanding the effect of two-dimensional information updating, and the key findings in this work are significantly different from those with only demand information updating.

3. Model

Two firms (A and B) procure a commodity offshore to resell in a local market (or to produce substitutable products for the same downstream market). By convention, each firm sources the commodity and signs a long-term contract with an offshore supplier for the coming procurement horizon. In particular, each firm is required to determine, with its selected supplier, the contract form of either the contingent-price contract (CPC) or fixed-price contract (FPC). The determined contract form cannot be changed during the procurement horizon because it usually requires costly renegotiation. Then, the firm can place orders of specific quantities in subsequent periods under this contract. For expositional clarity, it suffices to consider a single order period of the procurement horizon. The qualitative insights will remain unchanged in the general case with multiple periods. In this study, we focus on the scenario where the firms are risk neutral. We extend the basic model in the appendix to incorporate the firms' risk aversion.

The firms engage in quantity competition in the local market. Given firm i's order quantity q_i $(i=A,B)$, the market clearing price for firm i is $p_i = a+\varepsilon_a - q_i - \gamma q_j$, where a is the deterministic intercept of the inverse demand function, ε_a measures the random term with $\varepsilon_a \sim N[0,\sigma_a^2]$, and $\gamma \in [0,1]$ stands for the competition intensity with a higher value indicating a greater degree of competition. We assume no other local supply of the commodity; thus, the uncertainty ε_a is purely caused by the local demand. We refer to a and ε_a as the market size and demand noise, respectively. Let s and w be the contract prices under the CPC and FPC, respectively. Both contract prices are linked to a publicly-known price index of the commodity. Specifically, at the time of contracting, the FPC price w is fixed based on the realized index, whereas the CPC price s remains open until the delivery date (e.g., Vale 2013). Define $s = \mu_s + \varepsilon_s$, where μ_s is the expected value and $\varepsilon_s \sim N[0,\sigma_s^2]$. The demand noise ε_a and random term ε_s are correlated with a coefficient $\rho \in [0,1)$, which is referred to as the *demand-price correlation*. Thus, $(\varepsilon_a,\varepsilon_s) \sim BN[0,0,\sigma_a^2,\sigma_s^2,\rho]$. When $\rho > 0$, the CPC price tends to be high if the demand is high and low otherwise. The positive demand-price correlation reflects a key characteristic of many global commodity markets, including iron ore and lithium carbonate. The standard deviation σ_a (σ_s) is assumed to be sufficiently smaller than its deterministic value a (μ_s), rendering the probability of a negative value of the market demand (CPC price) negligible. The CPC (FPC) has a cost advantage when $w > \mu_s$ ($w < \mu_s$).

We assume that firm i's demand forecast takes the following form: $f_i = \varepsilon_a + \varepsilon_i$, where $\varepsilon_i \sim N[0,\sigma_i^2]$, $i = A, B$. This form has been widely used to model noisy private signals (see, e.g., Grossman 1981, Mendelson and Tunca 2007). We further assume that ε_A and ε_B are independent of ε_a and ε_s (see, e.g., Chen and Tang 2015, Bimpikis et al. 2019). However, ε_A and ε_B are correlated with a coefficient $\eta \in [0,1)$ (e.g., Wu and Zhang 2014, Bimpikis et al. 2019), which is referred to as the *forecast correlation*. The smaller the value of η, the more different the data samples collected and the forecast methodologies adopted by the two firms. We use $\lambda_i \equiv \sigma_a^2/(\sigma_a^2+\sigma_i^2)$ to measure firm i's forecast accuracy. A larger value of λ_i represents a more accurate forecast of the firm. In the extreme case where $\lambda_i = 1$, the forecast perfectly reveals the uncertain demand. In the opposite extreme case where $\lambda_i = 0$, the forecast lacks valuable information on the uncertain demand, and the posterior distribution is identical to the prior. We exclude these two extreme cases and restrict our scope to $\lambda_i \in (0, 1)$. Competing in the same market, the firms are typically aware of their rivals' forecast capabilities and efforts. Hence, the assumption that a firm knows or can infer its rival's forecast accuracy is reasonable and has been adopted in the literature (e.g., Shin and Tunca 2010, Ha et al. 2011). All parameters are common knowledge except for the firms' private signals.

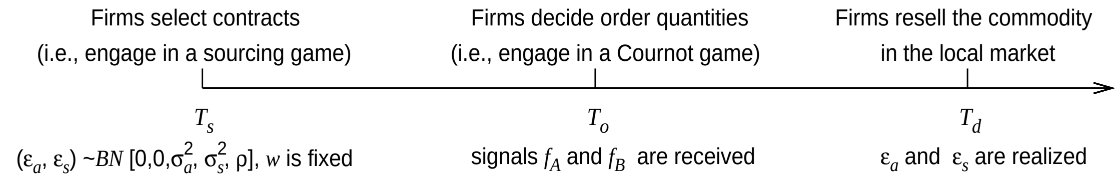

Figure 1 Decision and Information Timeline

The timing of the events is shown in Figure 1. At time T_s, the firms simultaneously select either the CPC or FPC, knowing the fixed FPC price w and the distributions of the demand noise ε_a and CPC price ε_s. That is, they effectively engage in a sourcing game. Each firm then places an order for the period from time T_o to T_d. Specifically, at time T_o, firm i uses its latest demand signal f_i to update information and chooses the order quantity q_i; that is, firm i solves $\max_{q_i} E[\pi_i|f_i]$, where $\pi_i = (p_i - s)q_i$ under the CPC and $\pi_i = (p_i - w)q_i$ under the FPC. To maintain the focus and for transparent analysis, we do not consider information updating using the realized index in the basic model, as empirical studies show that pure commodity prices cannot effectively predict future prices for short-run horizons[1]. Instead, we study an extension in Appendix A where the realized index is also used to update the belief on the unrealized CPC price and find that the qualitative results are robust. Finally, at time T_d, both the demand noise ε_a and random CPC price ε_s are realized. The firms receive their deliveries and resell the commodity in the local market. We follow the literature (e.g., Mendelson and Tunca 2007, Boyabatlı et al. 2011) to assume that neither firm holds up inventory at the end of the period, which is plausible for global commodity procurement characterized by significant price volatilities, quick capital turnovers, and expensive storage costs.

[1] For example, Alquist and Kilian (2010) find that forecasts based on pure futures and/or spot prices of crude oil cannot effectively predict future prices at the one- and three-month horizons. Chinn and Coibion (2014) show that at the three-month horizon, the prices of metals (e.g., aluminum, copper, lead, and tin) cannot be effectively predicted using futures prices, whereas the prices of natural gas and gasoline display limited predictive content.

The decision sequence in Figure 1 captures the essence of the global procurement process for many commodities. For example, an Asian importer may sign a quarterly CPC or FPC with a Brazilian iron ore supplier in June. The quarterly contract guarantees a reliable and quality supply of iron ore and allows both parties to plan their operations accordingly. From July to September, the importer places monthly orders of specific quantities according to its latest demand forecasts. Each order arrives at the local market after going through the process of cargo collection, port loading, ocean transport, and customs clearance, which takes approximately two months. If the FPC is adopted, then the procurement price for all the monthly orders is the same and fixed at the signing of the contract in June, whereas with the CPC, the price of each order becomes known according to the IODEX at the time when the order reaches the port of the importer.

The following lemma presents the posterior means of the distributions for several key parameters. For brevity, we use the relative price volatility $\theta \equiv \sigma_s/\sigma_a$ instead of σ_s and define $\beta \equiv \eta\sigma_A\sigma_B/\sigma_a^2 = \eta\sqrt{(1-\lambda_A)(1-\lambda_B)/(\lambda_A\lambda_B)}$.

Lemma 1 *Given a demand signal f_i, we have $E[\varepsilon_a|f_i] = \lambda_i f_i$, $E[\varepsilon_s|f_i] = \rho\theta\lambda_i f_i$, and $E[f_j|f_i] = (1+\beta)\lambda_i f_i$, where $i, j = A, B$, and $i \neq j$.*

Lemma 1 demonstrates how the demand signal f_i is used to update both the demand noise ε_a and random CPC price ε_s. We refer to $E[\varepsilon_a|f_i] = \lambda_i f_i$ and $E[\varepsilon_s|f_i] = \rho\theta\lambda_i f_i$ as the demand-side and cost-side information updating, respectively. Note that the cost-side information updating depends on the demand-price correlation ρ and price volatility θ. If $\rho = 0$, then the cost-side information updating does not occur because $E[\varepsilon_s|f_i] = 0$.

There are four Cournot subgames depending on the firms' contract selections at time T_s. Let the letter C (F) stand for the CPC (FPC). We use CC, CF, FC, and FF to denote the subgames, with the first (second) letter representing the contract selected by firm A (B). Used as superscripts, CC, CF, FC, and FF refer to the Cournot equilibria in the corresponding subgames. For instance, Π_A^{FC} denotes the equilibrium ex ante profit of firm A in the FC subgame, in which firm A adopts the FPC, whereas firm B uses the CPC. Table 1 summarizes the notations in our model.

Table 1 Model Notation

p_i	Market clearing price for firm i
q_i	Order quantity of firm i
a	Deterministic market size
ε_a	Demand noise, $\varepsilon_a \sim N[0, \sigma_a^2]$
γ	Competition intensity, $\gamma \in [0,1]$
w	Deterministic FPC price
s	CPC price, $s = \mu_s + \varepsilon_s$, $\varepsilon_s \sim N[0, \sigma_s^2]$
ρ	Demand-price correlation, $\rho \in [0,1)$
f_i	Signal of firm i, $f_i = \varepsilon_a + \varepsilon_i$, $\varepsilon_i \sim N[0, \sigma_i^2]$
η	Forecast correlation, $\eta \in [0,1)$
λ_i	Forecast accuracy of firm i, $\lambda_i = \sigma_a^2/(\sigma_a^2 + \sigma_i^2)$
θ	Relative price volatility, $\theta = \sigma_s/\sigma_a$
Π_i^k	Ex ante profit of firm i in subgame k

4. Cournot Subgames

In this section, we solve for the equilibrium quantity decisions made at time T_o for each of the Cournot subgames and then derive the corresponding ex ante profits of the firms.

4.1. Equilibrium Quantity Decisions

Define $\kappa \equiv 1/[4 - \gamma^2 \lambda_A \lambda_B (1+\beta)^2]$ for brevity. It can be shown that $\kappa > 0$.

Lemma 2 *There exists a unique Bayesian Nash equilibrium for each Cournot subgame, and the equilibrium order quantities are given as follows:*

(*a*) *for the FF subgame,*

$$q_i^{FF} = \frac{a - w}{2 + \gamma} + [2 - \gamma \lambda_j (1+\beta)] \kappa \lambda_i f_i, \qquad i, j = A, B, \quad i \neq j; \tag{1}$$

(*b*) *for the CC subgame,*

$$q_i^{CC} = \frac{a - \mu_s}{2 + \gamma} + (1 - \rho\theta)[2 - \gamma \lambda_j (1+\beta)] \kappa \lambda_i f_i, \qquad i, j = A, B, \quad i \neq j; \tag{2}$$

(*c*) *for the FC subgame,*

$$q_A^{FC} = \frac{(2-\gamma)a - 2w + \gamma \mu_s}{4 - \gamma^2} + [2 - (1-\rho\theta)\gamma \lambda_B (1+\beta)] \kappa \lambda_A f_A, \tag{3}$$

$$q_B^{FC} = \frac{(2-\gamma)a - 2\mu_s + \gamma w}{4 - \gamma^2} + [2(1-\rho\theta) - \gamma \lambda_A (1+\beta)] \kappa \lambda_B f_B. \tag{4}$$

Lemma 2 shows that each equilibrium quantity consists of a base quantity (i.e., the first term) and an information quantity (i.e., the second term). We refer to the absolute value of the coefficient of the signal f_i as the *adjustment magnitude*, and its sign as the *adjustment direction*, which reflects whether the information quantity responds positively or negatively to the signal.

When $\gamma = 0$, the equilibrium quantities described in Lemma 2 reduce to the optimal quantities of a monopolist: $q_i^F = (a - w)/2 + \lambda_i f_i/2$ under the FPC and $q_i^C = (a - \mu_s)/2 + (1 - \rho\theta)\lambda_i f_i/2$ under the CPC. We find that compared with q_i^F, the additional factor $(1 - \rho\theta)$ in q_i^C not only changes the adjustment magnitude but may also reverse the adjustment direction. We refer to this factor as the *price-learning effect* of the CPC. This effect can be attributed to the opposing effects of the demand- and cost-side information updating on the quantity: A positive demand signal increases the quantity based on the demand-side updating but reduces it through the cost-side updating. When $\theta > 1/\rho$, a positive (negative) demand signal implies a significantly high (low) perceived CPC price and, consequently, the firm reduces (increases) its information quantity in response to the high (low) perceived procurement cost. Thus, the price-learning effect reverses the adjustment direction since the cost-side updating dominates the demand-side updating. Furthermore, when $\theta > 2/\rho$, the adjustment magnitude under the CPC is greater than that under the FPC. If the CPC is used, a sufficiently large price volatility requires the firm to be more sensitive to the procurement cost. Hence, the firm primarily relies on the cost-side information updating to determine its quantity, leading to a significant adjustment magnitude. By contrast, the firm under the FPC has to adjust its quantity solely based on the demand-side information updating, resulting in a small adjustment magnitude. When $\theta < 2/\rho$, the adjustment magnitude under the CPC becomes smaller because the demand-side information updating partially offsets the cost-side information updating.

Under competition (i.e., $\gamma \neq 0$), the influence of the price-learning effect on a firm's ordering decision also depends on the contract form adopted by its rival. In the CC subgame, each firm adjusts its quantity according to its updated belief on both the demand and CPC price and to its anticipation of the rival's updates. Consequently, the price-learning effect impacts the two firms' decisions uniformly; that is, it reverses their adjustment directions when $\theta > 1/\rho$ and amplifies their adjustment magnitudes when $\theta > 2/\rho$, aligning with the findings in the monopoly case. In the FC subgame, asymmetric information on the procurement costs arises: Firm B knows firm A's cost w whereas firm A needs to infer firm B's perceived cost. Thus, to adjust the quantity, firm A updates its belief on the demand and infers the rival's perceived demand and CPC price, whereas firm B updates its belief on both the demand and CPC price and infers the rival's perceived demand. As a result, the price-learning effect of the CPC affects the adjustment magnitudes of the firms differently and, in particular, may result in opposite adjustment directions. For example, when $\lambda_A = \lambda_B = 0.5$, $\rho = 0.5$, $\eta = 0.2$, and $\gamma = 0.8$, firm A always responds positively to f_A, while firm B responds negatively to f_B if $\theta > 1.52$. Finally, we note that unlike the CC subgame, the competition intensity in the FC subgame also plays a critical role in influencing the impact of the price-learning effect on the adjustment directions and magnitudes. Specifically, given a price volatility, a higher competition intensity will more likely lead to opposite adjustment directions.

Remark 1 *The price-learning effect of the CPC has a two-fold impact on a firm's order quantity decision. First, compared with the FPC, the price-learning effect leads to a strong response to market changes if the price volatility is sufficiently large and a weak response otherwise. Second, in the FC subgame, the price-learning effect may enable the firms to adjust their respective order quantities in opposite directions, helping to prevent excessively high or low market clearing prices and, consequently, mitigating the competition between the two firms.*

4.2. Equilibrium Ex Ante Profits

Based on the equilibrium quantity decisions, we can obtain the firms' ex ante profits at time T_s by taking expectation with respect to the demand signals f_A and f_B:

$$\Pi_i^{FF} = \frac{(a-w)^2}{(2+\gamma)^2} + [2-\gamma\lambda_j(1+\beta)]^2\kappa^2\lambda_i\sigma_a^2, \quad i,j=A,B, \ \ i \neq j, \tag{5}$$

$$\Pi_i^{CC} = \frac{(a-\mu_s)^2}{(2+\gamma)^2} + (1-\rho\theta)^2[2-\gamma\lambda_j(1+\beta)]^2\kappa^2\lambda_i\sigma_a^2, \quad i,j=A,B, \ \ i \neq j, \tag{6}$$

$$\Pi_A^{FC} = \frac{[(2-\gamma)a-2w+\gamma\mu_s]^2}{(4-\gamma^2)^2} + [2-(1-\rho\theta)\gamma\lambda_B(1+\beta)]^2\kappa^2\lambda_A\sigma_a^2, \tag{7}$$

$$\Pi_B^{FC} = \frac{[(2-\gamma)a-2\mu_s+\gamma w]^2}{(4-\gamma^2)^2} + [2(1-\rho\theta)-\gamma\lambda_A(1+\beta)]^2\kappa^2\lambda_B\sigma_a^2. \tag{8}$$

We can see that each equilibrium ex ante profit consists of two terms. The first term decreases in the firm's own expected contract price (w or μ_s) and is thus referred to as the *efficiency component*. The second term results from the information quantity and is referred to as the *information benefit*. In the FF subgame, the firms derive an information benefit since the quantities determined based on the demand-side information updating align more closely with the demand. In the CC subgame, a sufficiently large price volatility (i.e., $\theta > 2/\rho$) compels the firms to primarily rely on the cost-side information updating to adjust the quantities. This adjustment leads to a better alignment with the CPC price and, consequently, provides greater information benefits to the firms compared to matching the quantities solely with the updated demand in the FF subgame.

5. Implications of Price Volatility and Forecast Accuracy

Based on the Cournot equilibria characterized in the previous section, we now investigate the effects of price volatility and forecast accuracies on the firms' profit performances.

5.1. Price Volatility

In the CC or FC subgame, there is no cost-side information updating when $\rho = 0$. Consequently, neither firm's profit is affected by the price volatility of the CPC. However, when $\rho > 0$, a firm can use its signal to update its belief about the CPC price, generating the price-learning effect.

Proposition 1 *Suppose $\rho > 0$. (a) In the CC subgame, Π_A^{CC} and Π_B^{CC} increase in θ if $\theta > 1/\rho$ and decrease in θ if $\theta < 1/\rho$. (b) In the FC subgame and $\gamma \neq 0$, Π_A^{FC} increases in θ if $\theta > \theta_A^T$ and decreases in θ if $\theta < \theta_A^T$, whereas Π_B^{FC} increases in θ if $\theta > \theta_B^T$ and decreases in θ if $\theta < \theta_B^T$, where*

$$\theta_A^T = \frac{-2 + \gamma\lambda_B(1+\beta)}{\rho\gamma\lambda_B(1+\beta)}, \qquad \theta_B^T = \frac{2 - \gamma\lambda_A(1+\beta)}{2\rho}. \tag{9}$$

Proposition 1(a) states that in the CC subgame, an increase in price volatility is beneficial to both firms when the value of $\rho\theta$ is relatively large. Recall from Lemma 1 that a larger price volatility enhances the effect of the cost-side information updating as $E[\varepsilon_s|f_i] = \rho\theta\lambda_i f_i$. When $\theta > 1/\rho$, the effect of the cost-side information updating dominates that of the demand-side information updating so that an increase in price volatility leads to more significant adjustments at both firms, which helps better match their quantities with the actual procurement cost. However, when $\theta < 1/\rho$, an increase in price volatility weakens the price-learning effect of the CPC, which is detrimental to both firms. This is because the effect of the demand-side information updating is offset by the enhanced effect of the cost-side information updating.

In contrast to the CC subgame, the impact of price volatility on the firms' ex ante profits in the FC subgame is different because the price-learning effect affects the two firms' ordering decisions differently. Consider an example with $\lambda_A = \lambda_B = 0.5$, $\rho = 0.5$, $\eta = 0.1$, and $\gamma = 1$. Firm A's information benefit always increases in the price volatility whereas firm B's increases only when $\theta > 1.45$. When θ increases from 2 to 4, firm A's information quantity changes from $0.27f_A$ to $0.34f_A$ whereas firm B's changes from $-0.07f_B$ to $-0.34f_B$. Clearly, the increase in price volatility enhances the adjustment magnitudes of both firms and thereby improves their information benefits. Note that if $\theta = 4$, the information quantities in q_A^{CC} and q_B^{CC} are $-0.2f_A$ and $-0.2f_B$, respectively. This indicates that the stronger responses of the quantities in the FC subgame are enabled by opposite adjustment directions, which dampen the competition between the firms. We further find that the threshold θ_A^T increases whereas θ_B^T decreases in γ, indicating that a higher competition intensity makes firm A (B) less (more) likely to benefit from an increase in price volatility.

Anecdotal industry evidence suggests that the price-learning effect of the CPC has not been recognized by managers when making commodity procurement decisions. Many firms adopt various financial hedging strategies to counter the price volatility associated with the CPC. For instance, futures contracts are frequently used by importers in the global commodity trade. Importers may take long futures positions immediately after signing the CPC (e.g., Hull 2009); hence, they usually make their ordering decisions based on financially hedged price volatilities. In this study, a decrease in the price volatility in the CC (FC) subgame is equivalent to the situation where both firms (firm B) adopt a financial hedging strategy. Our finding indicates that the hedging and ordering decisions without considering the price-learning effect of the CPC could be suboptimal because it may hinder importers' responsiveness to market changes.

The above analysis offers a new explanation for utilizing the CPC in a horizontal competitive setting. This explanation differs from the risk-sharing mechanism of the CPC that allows the members of a vertical supply chain to redistribute input price risks (e.g., Goel and Tanrisever 2017, Kouvelis et al. 2018). To better utilize the CPC in our model setting, it is worth emphasizing the effect of the demand-price correlation ρ, based primarily on which the price-learning effect arises. For instance, how to select an underlying index is critical in the global iron ore trade. Currently, the IODEX is commonly adopted. However, the call for a China-based index has intensified in recent years (e.g., Lian and Mason 2018), because it better reflects the Chinese market demand. We can further show that a higher value of ρ reduces the thresholds of θ in Proposition 1 so that the value of the CPC can more likely be achieved in both the CC and FC subgames.

Remark 2 *Our study reveals the bright side of price volatility when the CPC is used: It enhances firms' capabilities to respond to market changes, including both demand and procurement price. Such an effect resembles various strategies in the literature that provide extra operational flexibilities to mitigate demand uncertainty faced by firms. Examples include sourcing later to acquire accurate information (Wu and Zhang 2014), differentiation or delaying production (Wang et al. 2014), and using additional replenishment options (Lin and Parlaktürk 2012). With the CPC, a firm only needs to adjust its quantity based on two-dimensional information updating without the need to postpone its operational commitment. Thus, implementing the CPC is relatively easy in practice.*

5.2. Forecast Accuracy

We proceed to study how forecast accuracies affect the firms' ex ante profits. For clarity of analysis, we focus on the case where there is no forecast correlation, that is, $\eta = 0$; see Li and Zhang (2008) and Chen and Tang (2015) for similar assumptions. Recall $\lambda_i \equiv \sigma_a^2/(\sigma_a^2 + \sigma_i^2)$ measures firm i's forecast accuracy. We fix σ_a and vary σ_i to investigate the impact of the firm's forecast accuracy.

In the CC or FF subgame, a firm's forecast accuracy improvement always benefits itself but hurts its rival because it enhances the firm's adjustment magnitude but weakens that of its rival. In the FC subgame, a firm can still benefit from its own forecast accuracy improvement. However, the impact of a firm's forecast accuracy on its rival becomes quite different.

Proposition 2 *In the FC subgame with $\eta = 0$ and $\rho > 0$, Π_i^{FC} increases in λ_j if $\theta > \frac{2-\gamma\lambda_A}{2\rho}$ and decreases in λ_j if $\theta < \frac{2-\gamma\lambda_A}{2\rho}$, where $i, j = A, B$, and $i \neq j$.*

Proposition 2 shows that in the FC subgame with a sufficiently large price volatility θ, a firm can always benefit from its rival's forecast accuracy improvement, regardless of the firm's contract type. This finding suggests that, under certain conditions, a "win–win" outcome can be achieved by the competing firms if one of them improves its forecast accuracy. By contrast, with the absence of the price-learning effect (i.e., $\rho = 0$), the firms in the FC subgame cannot adjust their information quantities oppositely; thus, the "win–win" outcome is no longer possible. Although Proposition 2 requires $\eta = 0$, we find through extensive numerical experiments that the result still holds for $\eta > 0$ when the firms can adjust information quantities in opposite directions.

Remark 3 *The existing literature (e.g., Vives 1984) demonstrates that in an FF game, a firm would always be hurt by the improvement of its rival's demand forecast accuracy. This result also holds for the CC subgame in our model setting. By contrast, a firm in the FC subgame may benefit from the improvement of its rival's demand forecast accuracy because the price-learning effect under contract differentiation allows the firms to adjust the information quantities oppositely, so that both firms' adjustment magnitudes can increase in the demand forecast accuracy of one firm when the price volatility is sufficiently large.*

The above finding suggests that taking the advantage of the rival's forecast accuracy improvement can be an incentive for a firm to adopt differentiated contracts, especially when facing a large price volatility. In practice, information acquisition is usually costly. In the CC or FF subgame, firm A's forecast accuracy improvement benefits itself but hurts firm B. To avoid being hurt, firm B has to improve its own forecast accuracy. Consequently, competition may drive both firms to overinvest in demand forecasting, as found in Shin and Tunca (2010) for a different setting. However, the firms in the FC subgame do not need to competitively improve their respective forecast accuracies when the price volatility is relatively large. Instead, adopting differentiated contracts may be a wise choice for them, especially for those whose information acquisition is highly costly.

6. Sourcing Games

This section explores the equilibrium of the sourcing game occurring at time T_s. We will begin by analyzing the special case with $\rho = 0$ as a benchmark for future comparison.

Proposition 3 *Suppose $\rho = 0$. (a) When $w = \mu_s$, CC, CF, FC, and FF are the sourcing equilibria; and (b) the unique sourcing equilibrium is CC when $w > \mu_s$ and FF when $w < \mu_s$.*

When $\rho = 0$, the price-learning effect of the CPC does not exist and thus the two firms achieve the same information benefit in all the subgames. Furthermore, when the expected procurement costs of the CPC and FPC are the same (i.e., $w = \mu_s$), the efficiency components in all the subgames are also identical. Hence, the CPC and FPC are indifferent to the firms. However, both firms select the CPC if $w > \mu_s$ but the FPC if $w < \mu_s$. Clearly, without two-dimensional information updating, cost efficiency would be the deciding factor for contract choice. We note that the firms' forecast accuracies play no role in their contract choices when the price-learning effect does not exist.

6.1. Sourcing Equilibrium when $w = \mu_s$

We now examine how the price-learning effect of the CPC changes the sourcing equilibrium when $w = \mu_s$. It suffices to only consider the case $\lambda_A \le \lambda_B$. We define two thresholds of the correlation η:

$$\psi_i^C = \frac{\sqrt{\lambda_i}[2 - \rho\theta - \gamma\lambda_j(1 - \rho\theta)]}{\gamma(1 - \rho\theta)\sqrt{\lambda_j(1 - \lambda_A)(1 - \lambda_B)}}, \tag{10}$$

and

$$\psi_i^F = \frac{\sqrt{\lambda_i}(2 - \rho\theta - \gamma\lambda_j)}{\gamma\sqrt{\lambda_j(1 - \lambda_A)(1 - \lambda_B)}}, \quad i, j = A, B, \ i \ne j. \tag{11}$$

For conciseness, we focus on the non-boundary cases $\eta \ne \psi_i^C$ and $\eta \ne \psi_i^F$.[2]

Proposition 4 *Suppose $w = \mu_s$, $\rho > 0$, and $\gamma \ne 0$. (a) When $\theta < 2/\rho$, the unique sourcing equilibrium is FF if $\eta < \psi_A^F$, CF if $\psi_A^F < \eta < \psi_B^F$, and CF and FC are the sourcing equilibria if $\eta > \psi_B^F$. (b) When $\theta > 2/\rho$, the unique sourcing equilibrium is CC if $\eta < \psi_A^C$, FC if $\psi_A^C < \eta < \psi_B^C$, and CF and FC are the sourcing equilibria if $\eta > \psi_B^C$.*

[2] For example, when $\eta = \psi_A^C$, it can be verified that both CC and FC are the sourcing equilibria. We can view the boundary case $\eta = \psi_A^C$ as the cases with $\eta - \psi_A^C \to 0^+$ and $\eta - \psi_A^C \to 0^-$, which can be technically analyzed as the interior cases of $\eta > \psi_A^C$ and $\eta < \psi_A^C$, respectively.

Proposition 4 shows that the sourcing equilibria for $\rho > 0$ are more involved than the case $\rho = 0$ because the price-learning effect of the CPC influences the firms' adjustment magnitudes and directions. Note from Lemma 2 that the market size a only affects the base quantities, which remain the same in all the subgames when $w = \mu_s$; thus, it plays no role in the sourcing equilibria. We may use Figure 2 to illustrate the sourcing equilibria, in which $\rho\theta$ is used as the horizontal axis because these two parameters affect the thresholds ψ_i^C and ψ_i^F in the same way. We observe from Plot (a) that $\psi_A^C = \psi_B^C$ and $\psi_A^F = \psi_B^F$ in the symmetric case (i.e., $\lambda_A = \lambda_B$).

Figure 2 depicts how different parameters affect the equilibria. First, we find from Plot (a) that both firms adopt the CPC if $\rho\theta$ is sufficiently large. In this case, the price-learning effect of the CPC enhances both firms' adjustment magnitudes compared with the FPC (see Remark 1). Hence, both firms seek the stronger responsiveness of the CPC. By contrast, if $\rho\theta$ is sufficiently small, the price-learning effect dampens the responsiveness of the CPC. Thus, both firms pursue the stronger responsiveness of the FPC. Interestingly, asymmetric equilibria (i.e., CF and FC) arise when $\rho\theta$ is around 2, although the firms are ex-ante symmetric.

Remark 4 *Wu and Zhang (2014) find that the reduced information correlation leads to asymmetric sourcing equilibria. By contrast, what drives asymmetric equilibria here is the opposite adjustment directions enabled by the price-learning effect of the CPC, which enhance the firms' responses to market changes and dampen the competition.*

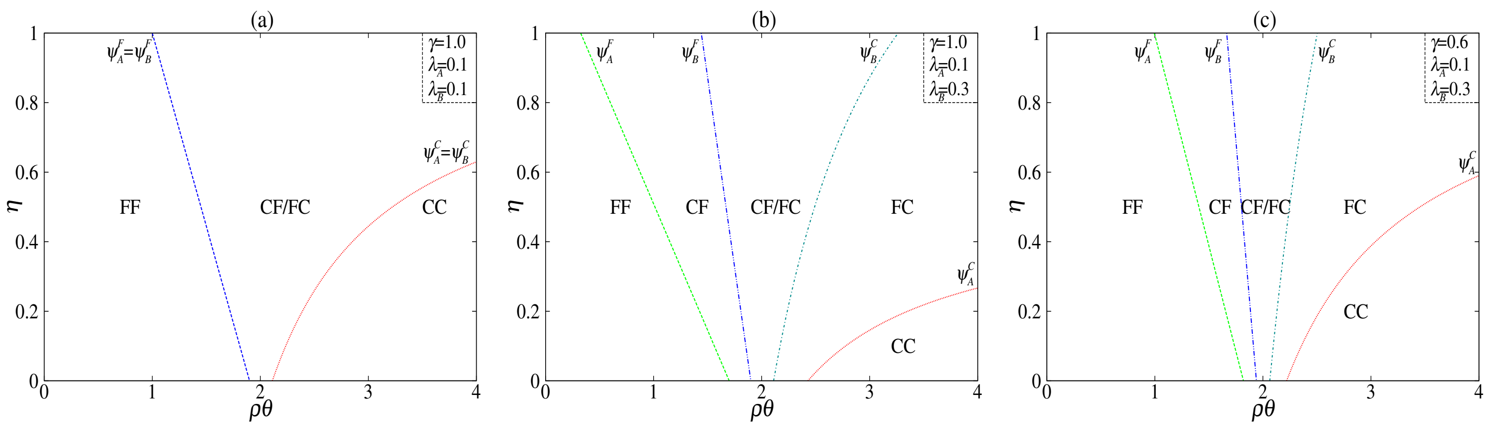

Figure 2 **Sourcing Equilibria when** $w = \mu_s$

Second, by comparing Plot (b) with $\lambda_B = 0.3$ and Plot (a) with $\lambda_B = 0.1$, we find that contract differentiation is more likely to happen under asymmetric forecast accuracies. For example, if $\rho\theta = 3$ and $\eta = 0.4$, the unique equilibrium is CC with symmetric accuracies but FC with asymmetric accuracies. Clearly, the increase in λ_B drives firm A to switch from the CPC to the FPC, whereas firm B remains with the CPC. The reason is that firm A, as the inferior forecaster, can benefit from its rival's forecast accuracy improvement under differentiated contracts (see Proposition 2), whereas the superior forecaster continues to pursue the stronger responsiveness of the CPC. Again, the role of the forecast accuracies in the firms' contract choices is due to the price-learning effect.

Third, we investigate the effect of the competition intensity γ on the sourcing equilibria by comparing Plot (c) with Plot (b). We find that when γ decreases from 1 to 0.6, the thresholds ψ_i^C and ψ_i^F converge to $\rho\theta = 2$. Consequently, the regions for the asymmetric equilibria shrink, whereas the regions for the CC and FF equilibria expand. The result confirms that a high competition intensity is the key driving force for the asymmetric contract choices in equilibrium. In particular, without competition, the monopolist adopts the CPC if $\rho\theta > 2$ and the FPC otherwise.

Finally, we examine the impact of the forecast correlation η, and find that the larger the forecast correlation, the more likely differentiated contracts are adopted. A larger value of η means that the firms' demand signals f_A and f_B overlap more and contain less idiosyncratic information for each firm. Thus, the firms are more likely to choose similar order quantities. To dampen the competition and achieve responsiveness to market change in the ordering stage, it is optimal for the firms to differentiate their contract forms.

The difference between Π_i^{CF} and Π_i^{FC} can be verified to be extremely small when CF and FC are the sourcing equilibria. Thus, we can summarize a guideline that firms may follow in practice. A superior forecaster should always pursue the stronger responsiveness by adopting the CPC when $\rho\theta > 2$ but the FPC when $\rho\theta < 2$, which is consistent with the contract choice in the monopoly case. By contrast, an inferior forecaster also needs to consider the value of contract differentiation when both the competition intensity γ and forecast correlation η are sufficiently large and the value of $\rho\theta$ is moderate; in this case, it should select the CPC when $\rho\theta < 2$ but the FPC when $\rho\theta > 2$.

6.2. Sourcing Equilibrium when $w \neq \mu_s$

We now present the sourcing equilibria when the FPC has a cost advantage (i.e., $w < \mu_s$). Define

$$\phi_i^C = \frac{\mu_s + (1-\gamma)w}{2-\gamma} + \frac{(2-\gamma)(2+\gamma)^2\rho\theta\lambda_i\sigma_a^2[\gamma\lambda_j(1+\beta) - 2 + \rho\theta]}{(\mu_s - w)[4-\gamma^2\lambda_A\lambda_B(1+\beta)^2]^2}, \tag{12}$$

and

$$\phi_i^F = \frac{w + (1-\gamma)\mu_s}{2-\gamma} + \frac{(2-\gamma)(2+\gamma)^2\rho\theta\lambda_i\sigma_a^2[\gamma\lambda_j(1-\rho\theta)(1+\beta) - 2 + \rho\theta]}{(\mu_s - w)[4-\gamma^2\lambda_A\lambda_B(1+\beta)^2]^2}, \quad i,j = A,B, \; i \neq j. \tag{13}$$

Proposition 5 *Suppose $w < \mu_s$ and $\rho > 0$. The unique sourcing equilibrium is CC if $a < \phi_A^F$, FF if $a > \max\{\phi_A^C, \phi_B^C\}$, FC if $\phi_A^F < a < \phi_B^F$ or $\phi_A^C < a < \phi_B^C$, CF if $\phi_B^C < a < \phi_A^C$, and CF and FC are the sourcing equilibria if $\phi_B^F < a < \min\{\phi_A^C, \phi_B^C\}$.*

Figure 3(a) illustrates the sourcing equilibria characterized in Proposition 5 with $w = 7.75$, $\mu_s = 7.8$, $\lambda_A = \lambda_B = 0.1$, $\gamma = 1$, $\sigma_a = 0.4$, and $\eta = 0.1$. We find that when $\rho\theta < 1.8$, FF is always the unique sourcing equilibrium regardless of the market size because the FPC has both cost and responsiveness advantages over the CPC. When $\rho\theta > 2$, the firms face a trade-off between the stronger responsiveness of the CPC and the cost saving of the FPC. If the market size is sufficiently large, then both firms should seek the cost efficiency of the FPC. As the market size shrinks, the firms initially adopt differentiated contracts (i.e., CF or FC) to dampen the competition and eventually switch to the CPC to pursue the responsiveness. This finding suggests that with large values of the price volatility θ and demand-price correlation ρ, the firms in a small market should give higher priority to the CPC because the CPC provides a way to utilize the cost-side information updating (i.e., it acts as a type of quick response strategy, as noted in Remark 2) or to dampen the competition through contract differentiation.

When λ_B increases from 0.1 to 0.2, Plot (a) shifts to Plot (b). We find that the regions for the CC and FF equilibria shrink, whereas the regions for asymmetric equilibria expand significantly. Specifically, when $\rho\theta$ is greater than 2, the inferior forecaster switches from the CPC to the FPC to dampen the competition, but the superior forecaster stays with the CPC to enjoy the responsiveness

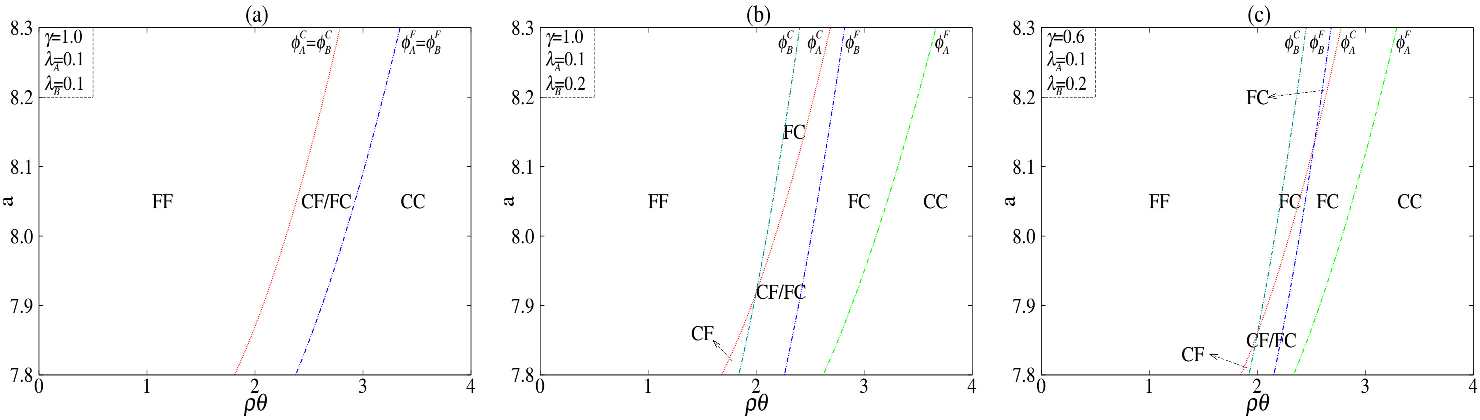

Figure 3 Sourcing Equilibria when $w < \mu_s$

benefit. By contrast, when $\rho\theta$ is slightly smaller than 2, the superior forecaster under contract differentiation seeks the stronger responsiveness of the FPC. When the competition intensity γ decreases from 1 in Plot (b) to 0.6 in Plot (c), the regions for asymmetric equilibria shrink but those for the CC and FF equilibria expand. In particular, without competition, the monopolist adopts the CPC only if $\rho\theta > 2$ and the market size is smaller than a threshold.

We discuss the case $w > \mu_s$ in Appendix A and find that, although the sourcing equilibria differ from those in the case $w < \mu_s$, the underlying reasons behind the equilibria in these two cases are the same: The firms face a trade-off between cost efficiency and responsiveness, similar to the findings in Wu and Zhang (2014). However, different from Wu and Zhang (2014), where one strategy is always more responsive than the other, the CPC in our model setting reacts to demand information more responsively than does the FPC if the price volatility and demand-price correlation are relatively large and less responsively otherwise.

We summarize a guideline for $w \neq \mu_s$ as follows. The firms should pursue the cost efficiency of the contracts in a large market. In a small market, the firms should adopt the CPC if $\rho\theta$ is sufficiently large; otherwise, they should compare the cost savings when selecting a contract. When the FPC has a cost advantage, the firms should adopt the FPC if $\rho\theta$ is relatively small and differentiated contracts if $\rho\theta$ is moderate. By contrast, when the CPC has a cost advantage, they should choose the FPC if the competition intensity is sufficiently low; otherwise, they should adopt differentiated contracts and the superior forecaster should seek responsiveness.

7. Concluding Remarks

Motivated by the increasing popularity of the contingent-price contract (CPC) in global commodity markets, this study develops a game-theoretic model to examine the contract choices of competing firms between the CPC and fixed-price contract (FPC). The main findings and managerial insights from this study can be summarized as follows.

Our analysis shows that the interaction between price volatility and information updating creates a price-learning effect, which enables the firms' ordering decisions to be more responsive to market changes, especially when the price volatility is sufficiently large. Hence, the firms under the CPC may benefit from an increase in price volatility. This finding suggests that price fluctuations are not always detrimental to firms, and ordering decisions based on financially hedged price volatility are not necessarily preferred. In addition, it provides insights into how firms may utilize price volatility to their advantage, such as selecting a suitable underlying index in contract design. We also show that the improvement of a firm's forecast accuracy may benefit its rival under differentiated contracts. This result provides a new explanation for adopting differentiated contracts and suggests that competing firms can use contract differentiation to avoid over-investment in costly information acquisition.

We further explore the firms' contract choices between the CPC and FPC. Both firms should select contracts based on cost efficiency when the price-learning effect is absent. However, with the price-learning effect, the firms' contract choices could be significantly different. Specifically, a large price volatility drives firms to the CPC because it offers stronger responsiveness than the FPC. Interestingly, asymmetric sourcing equilibria may arise even if the firms are ex-ante symmetric. Additionally, a higher competition intensity favors contract differentiation. We also find that in a small market, the firms may seek responsiveness and contract differentiation rather than cost efficiency. Finally, this research suggests that the prevalence of the CPC in global commodity procurement could be explained by the price-learning effect, which improves firms' responsiveness to market changes and dampens competition at the same time.

We present several extensions to the basic model in Appendix A. First, we examine the variability of the firms' profits. We find that when the price volatility is sufficiently low, the CPC could result in a smaller profit variance than the FPC. This is because under the CPC, the positive demand-price correlation enables the price volatility to partially offset the demand uncertainty. However, the profit variance under the CPC becomes larger when the price volatility surpasses a threshold, as the price volatility plays a more significant role in determining the profit variance. Furthermore, we find that under both the CPC and FPC, risk aversion decreases the base quantity and adjustment magnitude. Nevertheless, the equilibrium contract structure remains unchanged as long as the risk aversion level is not significant. Second, we analyze the scenario with more than two firms and show that the key findings from the basic model continue to hold in the multi-firm setting. Third, we explore the situation where the firms could use both the CPC and FPC. It can be shown that the mixed contract option enables a firm to fully retain the responsiveness of the CPC and meanwhile improve cost efficiency. Hence, the mixed contract dominates the CPC alone. Finally, we investigate the supplier's contract preference and find that it is independent of price volatility because the procurement prices under both the CPC and FPC are exogenously given and the order quantities are determined by the buyers.

There are several promising directions for future research. First, this paper focuses on Cournot competition. It would be interesting to examine whether the findings continue to hold under price competition. Second, the firms' demand forecast accuracies are exogenously given in our model. It would be useful to see how the findings may change if the firms' forecast accuracy decisions are endogenized. Third, information sharing is an important research topic in the economics and operations literature. It is worth exploring whether competing firms may have incentives to form an alliance by pooling their private information when the CPC is used. Finally, we obtain some insights by using theoretical modeling and analysis. It would be valuable to verify empirically whether the findings hold in practice using real-world data. For example, future research could examine how price volatility and other important parameters affect the contract choices of competing firms in global commodity markets.

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