Smart energy storage management via information systems design

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ABSTRACT

Enabled by smart meters and Internet of Things (IoTs) technologies, we are now able to harness information systems and automatize the management of energy storages. Motivated by applications such as renewables integration and electrification of transportation, the paradigm shift towards smart-cities naturally inspires information systems design for energy storages. The goal of this paper is to understand the economic value of future market information to increase the efficiency of the energy market. From storages' perspective, we investigate energy storages' optimal decentralized buying and selling decisions under market uncertainty. Different potential policy interventions are discussed: (1) providing a publicly available market forecasting channel; (2) encouraging decentralized storages to share their private forecasts with each other; (3) releasing additional market information to a targeted subset of storages exclusively. Through these system level discussions, we evaluate different information management policies to coordinate storages' actions and improve their profitability. The key findings of this work include (1) a storage's payoff first increases then decreases in its private information precision. The over-precision in forecasts can lead to even lower payoffs; (2) communication among the storages could fail to achieve a coordinated effort to increase market efficiency; (3) it is optimal to release additional information to a subset of energy storages exclusively by targeted information release.

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1. Introduction

1.1. The economics of energy storages

Energy storages (ESs) are becoming increasingly common in the power system and are used in a host of services (Dunn et al., 2011; Pandžić et al., 2015). In essence, these devices *shift energy across time* through charging and discharging operations. Energy storage will become a critical component in the transmission network because of their ability to mitigate the uncertainty and variability in renewable resources. Recent studies have concluded that California would require up to a total of 186 GWh/22 GW network energy storage by 2050 (Solomon et al., 2014) and Northwest Power Pool would require a total of 10 GWh/1 GW network energy storage by 2019 to balance 14.4 GW of installed wind capacity (Kintner-Meyer et al., 2010). However, both of these studies did not focus on the economics of storage. In particular, why storage owners would want to be in the system is not discussed in Solomon et al. (2014), and Kintner-Meyer et al. (2010) acknowledged that revenue for the owners may be thin.

Both regulators and system operators (SOs) agree that since the deployment of storage can reduce the operating cost of the grid, for-profit owners of storage should able to connect sufficient revenue to justify their investment and keep them in the system. For instance, California Independent System Operator (CAISO) roadmap states that "realizing the full revenue opportunities consistent with the value ES can provide" is a priority of system design (CAISO, 2014). At the same time, Federal Energy Regulatory Commission (FERC) Order No. 792 specifically identifies storage as small generators and instructs that they should be able to earn their fair share of revenue (FERC, 2013). In

line with CAISO (2014) and FERC (2013), this paper investigates how storages should be operated to maximize their revenue. In particular, because of the importance of the role *uncertainty* plays in a system with storage, we discuss the *role of information* on the operation of a set of storages.

A fundamental impact of renewable integration on the electricity market is the so-called "merit order effect": the supply of renewable energy has negligible marginal costs and in turn reduces the spot equilibrium price (Acemoglu et al., 2015; Zhang et al., 2015; Gil and Lin, 2013). Naturally, the variability and uncertainty in renewable resources lead to dynamically varying electricity prices. Therefore, forecasting of these prices becomes necessary for storages to make buying or selling decisions. In addition, it is unlikely for a few large entities to own most of the storages. For example, the required storage capacity in CAISO will likely be achieved via many smaller storage owners.

1.2. "Smart" energy storages, information and privacy management

To present a clear picture and pin down the heart of the problem, we start the paper by describing the energy storage, while abstracting away from the energy generation, consumption and the power grid. We delay the description of the bigger picture in the extension, where we had considered a generalized model, integrating the power generation and consumption with the storage component. The integrated agents, known as energy "prosumer", will generate, store and consume energy, connected through a common market.

The informational intervention is possible through recent technology such as "smart" energy storage, which refers to a system wherein the batteries charge at night and release electricity at peak times during the day to shave load. By feeding market data to the prosumers, some of the agents become more "informed" than others. In this context, the "informed storages" correspond to the smart storage while the uninformed storages correspond to the regular ones, which either do not have access to the market data or do not utilize it for load-shaving. Similarly, due to privacy concern, the prosumers do not communicate with each other and there is no information sharing. It is not clear, however, this privacy concern is beneficial to the prosumers or not, in terms of aggregate welfare.

With the adoption of smart meters, policy-maker can now regulate the energy market indirectly via information systems to increase the market efficiency. The applications ranging from power plants, manufacturers, households and even electric vehicles, contributing towards a coordinated effort for sustainable operations in the context of smart-cities.[1] In the context of "smart energy storages", our results will suggest, somewhat surprisingly, it is not necessarily better for all energy storages to be "smart", even if we ignore their technology costs; It is optimal to select some but not all storages to be smart, by putting up certain degree of privacy constraint.

The goal of this paper is to understand the economic value of *future market information*, as multiple storages compete with each other and try to mitigate market uncertainty by *forward-looking strategies*. In particular, we address the following research questions:

- When the energy prices are both uncertain and dynamic, what are the load-shaving behaviors of those "smart" energy storages?
- At a system level, what is a good information management policy (privacy vs. data-sharing) to coordinate storages' actions and improve their profitability?

1.3. Research agenda

To answer these questions, we consider the operations of multiple independently owned storages in an oligopoly electricity market with Cournot competition. The Cournot competition models a setup where different firms compete by adjusting their production quantities. This model has been shown to be a good approximation to energy market, e.g., CAISO (Borenstein and Bushnell, 1999) and the New Zealand Market (Scott and Read, 1996). In this work, we adopt a price function that consists of three additive terms: a constant term, a term linear in the amount of storage energy injected into the market, and *a noise term that represents the uncertain exogenous price shocks in the market*. We study how different ways of information dissemination about the price shock impact the efficiency of the market. Our main contributions in this paper are as follows:

1. To our best knowledge, this is the first model of a joint storage operation and forecasting under uncertainties, competitions and information asymmetries, which admits tractable analysis and interpretable structural results.
2. We show that giving more information to all of the players is not necessarily better. Namely, a public forecast about the price provided by the system operator leads to herding behaviors, thus revealing the market inefficiency driven by energy forecasts.
3. We conduct advanced analysis and studies on information mechanism design in the context of energy market and investigate the impact of exclusiveness of market information channel.

Firstly, we derive the optimal dynamic strategies for a single energy storage in closed-form. As the market uncertainty follows from an autoregressive process, the optimal dynamic strategies adapt to historical demand data as well as the accumulated information relevant to the future market forecast. Using a stylized model of two periods, we find that as a storage's reactions to forecasts are less responsive when the intertemporal demand correlation increases, the economic value of market information also decreases. For a similar reason, a storage's payoff also decreases in market uncertainty, as the storage's reactions to forecasts are also less responsive in this case. When the number of storages is large, the purchase or selling quantity responses are exaggerated and the over-precision in forecasts can lead to even lower payoffs, which decay to the order of inverse-square with respect to the number of storages.

Surprisingly, a storage's payoff first increases then decreases in its private information precision. When private information is scarce, the value of private information increases in its precision as it mitigates uncertainty. However, when the information precision further increases, the competition effect dominates and the payoff decreases. Therefore, we contribute to the energy economics literature by documenting this adverse effect of private market information.

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[1] For example, a company called "industrial.io" integrates data, streamlines deployments of new Industrial IoT assets, and hosts model predictive control algorithms to increase the energy efficiency for the city (https://www.ndustrial.io).

Extending this basic model, we demonstrate the value of public information in promoting the profitability of energy storage. Again, a storage's payoff decreases to the inverse-square of the number of storages. A storage's payoff first increases (due to the positive economic value) then decreases (due to the congestion effect) in the precision of the public market forecast. There will be no incentive for the storage to share information with each other. From this analysis, we find that communication among the storages fails to achieve a coordinated effort to increase market efficiency. To maintain the exclusiveness of their private forecasts, the storages should not be encouraged to share market information in this regime.

We also compare the payoff under public forecast with that under private forecasts. We find that the economic value of forecast under information sharing is (to an order of magnitude in the number of storages) lower than that under private forecasts. However, when the number of storages is finite, numerical analysis summarized it is possible that every storage is better off via information sharing. This regime is possible when each private forecast is extremely fuzzy, and pooling them together can amplify the market signal.

The rest of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 introduces our model setup. In Section 4, we carry out the analysis for two basic (simplified) models. In Section 5, we describe several policy intervention solutions. In Section 6, we extend the basic models in several directions. Section 7 concludes this paper with a discussion of future research directions.

2. Literature review

Our work contributes to the literature on oligopoly energy market. Recently, the integration of renewable energy into the economic discussion of finer-grained market structure has gained considerable attention in the energy economics literature, e.g., Wang et al. (2017) and Drabik et al. (2016). While the economic value of energy storages has been widely confirmed using empirical or computational approaches Benitez et al. (2008), few analytical or theoretical results are available concerning this complex economy under intrinsic market uncertainty with the integration of intermittent and stochastic renewable energy, e.g., Yu and Foggo (2017). Even less is known when such uncertainty (i.e., asymmetric information structure) itself being endogenous, depending on storages' decision to predict market uncertainty or cooperate by communication. Methodology-wise, we learn from a long stream of literature in economics and operations research on competitive market with incomplete information. The interaction of public and private information is studied in Colombo et al. (2014), while the uniqueness of this equilibrium prediction is guaranteed by Radner (1962). Our research is partly inspired by Acemoglu et al. (2015), wherein they also consider a competitive energy market with highly asymmetric information structures.

In terms of energy storage modeling, our model extends a similar work presented in Contreras-Ocana et al. (2017), which is perhaps most closely related to our work wherein they assume complete information and deterministic demand function. The fundamental inefficiency of such an energy market is driven by highly volatile local market conditions (e.g., electricity prices), for instance, due to intermittency in the renewable energy supply. For this reason, there is a growing literature on the use of an energy storage system to improve integration of the renewable energy (Dicorato et al., 2012; Shu and Jirutitijaroen, 2014). With this motivation (while abstracting away from the physical characteristics of the renewables), our model is closely related to this literature by incorporating both intertemporal variability and uncertainty (exogenous market price shocks). Given such an environment, storages will be foresighted and joint storage operation and forecasting have been reported consequently (Li et al., 2016; Haessig et al., 2015). While this literature is mostly simulation-based, our model admits tractable analysis and interpretable structural results.

Cournot model has been widely used as effective means to analyze and study electricity markets with incomplete competition. Optimal bidding strategies and modeling of imperfect information generator competition were presented in Wen and David (2001) Two Cournot models of imperfect competition were proposed in Hobbs (2001) for power producers in electricity markets. Willems (2002) presented the modeling of Cournot competition in an electricity market. It has been observed that the horizontal shifts in bid curves in wholesale electricity markets are consistent with Cournot competition (Lundin and Tangerås, 2017). The authors in Lundin and Tangerås (2017) introduced Cournot competition to the day-ahead wholesale market of the Nordic Power Exchange, Nord Pool. In Virasjoki et al. (2016), the authors analyzed the effects of energy storage on ramping cost and congestion based on a Nash–Cournot model in power systems with renewable power producers. Liu et al. (2018) and Tushar et al. (2015) are similar to our extension in modeling "prosumer" by combining generation, storage and consumption into a single agent. Yao and Venkitasubramaniam (2017) is also similar to our setup with incomplete information, while they focus on computing the equilibrium.

Beyond discussions on distributed storage operation and control, we put emphasis on information management at a system level. In a deregulated environment, it is natural to consider that the competing storages do not observe each other's private information (private energy price forecast). Therefore, the storages have to estimate each other's private forecast and conjecture on how each other's action depends on its forecast (Zhao and Khazaei, 2016). This strategic interaction poses technical challenge, which has not been studied in detail in the energy literature. A similar problem is studied in Kamalinia et al. (2014) in a different context (generation capacity expansion), wherein no structural results are available. Li and Shahidehpour (2005) and Langary et al. (2014) touch upon this topic in the context of generating companies' supply function equilibrium but resort to simulation. Furthermore, the private forecast in our model is sequentially revealed at every period, while the private information in the aforementioned literature is *static* (viewed as generation companies' attribute or type).

3. Model

Market structure. Consider n storages who purchase and sell substitutable energy through a common market. The storages, indexed by a set $I = \{1, 2, \ldots, n\}$, are homogeneous *ex ante* and engage in a Cournot competition. Let $d_i^{[t]}$ denote the energy purchased (when $d_i^{[t]} < 0$) or sold (when $d_i^{[t]} > 0$) by the ith storage at time t, and the aggregate storage quantity is denoted by $D^{[t]} = \sum_{i=1}^{i=n} d_i^{[t]}$. We model the demand side by assuming that the actual market clearing price $P^{[t]}(D^{[t]})$ is linear in $D^{[t]}$, i.e.,

$$P^{[t]}(D^{[t]}) = \beta^{[t]} - \gamma^{[t]} D^{[t]} + \eta^{[t]}, \quad \forall t \in T, \tag{1}$$

where a random variable $\eta^{[t]}$ captures the market uncertainty. $\beta^{[t]} > 0$ corresponds to market potential, which also captures market variability since $\beta^{[t]}$ is changing over time. $\gamma^{[t]} > 0$ (price elasticity) captures the fact that the market price decreases when the aggregate energy sold $D^{[t]}$ increases, as the market supply of energy increases.

To model storages' strategic interactions, our demand side setup corresponds to a scenario wherein storages are not price-takers but enjoy market power. This is supported by empirical evidence that energy prices vary in response to loads generation, especially when the storages are of sufficient scale (Sioshansi et al., 2009). Even if the storages are small-scaled, economics literature suggests that infinitesimal agents also act *as if* they are expecting the price–supply relationship (Osborne, 2005). Similar assumptions on storages' market power and price-anticipatory behavior are not uncommon in the literature (Sioshansi, 2010). Finally, with the integration of renewables and consequently the "merit order effect", the supply of renewable energy can drastically impact the spot equilibrium price considering its negligible marginal costs.

We assume that the market uncertainty follows an autoregressive process such that

$$\eta^{[t+1]} = \delta\eta^{[t]} + \epsilon_t, \quad \forall t \in T, \eta^{[1]} \sim N(0, \alpha^{-1}). \tag{2}$$

The parameter α is the initial information precision concerning the market uncertainty *a priori*. Standard assumptions for autoregressive process require that $|\delta| < 1$, where ϵ_t is exogenous shock $\epsilon_t \sim N(0, \zeta^{-1})$. We choose this stochastic process as it is among the simplest ones which capture intertemporal correlation while remaining realistic.

Storage model. Storages are agents who can buy energy at a certain time period and sell it at another. The net energy purchased and sold across time is required to be zero for every storage, i.e., $\sum_{t \in T} d_i^{[t]} = 0, \forall i \in I$. As we seek to emphasize the interaction between storages, we also abstract away from other operational constraints such as energy and/or power limits; instead, they are modeled by a cost function associated with each storage. The battery degradation, efficiency, and/or energy transaction costs of storage i are represented by the cost function $c_i(\cdot)$. This treatment is similar to that in Contreras-Ocana et al. (2017).[2]

We assume that $c_i(d) = \varepsilon^{[t]} \cdot d^2$ in the basic models. More realistically, $c_i(d)$ will be a power function $\varepsilon^{[t]} \cdot d^x$ wherein $x \in (1, 2)$, as it is known that as the depth of discharge increases, the costs of utilizing storage increase faster than linear. We can show that most of our results remain robust when the cost function $c_i(d)$ is generalized within this region. We choose $x = 2$ for a clear presentation of results. We also generalize the basic model to consider heterogeneous cost functions in the extensions. To summarize this discussion, the payoff of storage i can be expressed as

$$\pi_i\left(d_i^{[t]}, t \in T\right) = \sum_{t \in T}\left[P^{[t]}(D^{[t]}) \cdot d_i^{[t]} - \varepsilon^{[t]} \cdot \left(d_i^{[t]}\right)^2\right]. \tag{3}$$

Information structure and sequence of events. Storage i has a private forecast channel for the market condition. At the beginning of period t, storage i receives a private forecast $x_i^{[t]}$ with precision ρ, i.e., $x_i^{[t]} = \eta^{[t]} + \xi_i^{[t]}$, where $\xi_i^{[t]} \sim N(0, \rho^{-1})$, for $\forall i \in I$. The realizations of the forecasts are private, while their precision is common knowledge. In this paper, we use "forecast" and "information" interchangeably depending on the context.

At time t, the sequence of events proceeds as follows: (1) the storages observe (the realizations of) their private forecasts; (2) each storage decides the purchase or selling quantities based on their information, anticipating the rational decisions of the other storages; (3) the actual market price is realized and the market is cleared for period t.

4. Model analysis

4.1. Optimal dynamic strategies of a single storage

We begin by considering a single storage and thus dropping the subscript in this section. The optimal storage quantities are obtained by solving

$$\max_{d^{[t]}, t \in T} \sum_{t \in T} \mathbb{E}\left[P^{[t]} \cdot d^{[t]} - \varepsilon^{[t]} \cdot \left(d^{[t]}\right)^2 | X^{[t]}\right],$$

subject to

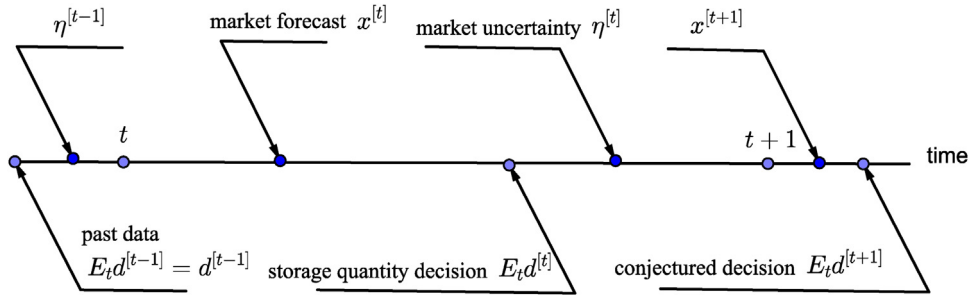$$\mathbb{E}\left[\sum_{t \in T} d^{[t]} | X^{[t]}\right] = 0, \tag{4}$$

for any sample path generated by $\{X^{[t]}\}$'s, wherein $X^{[t]} = \left\{x^{[1]}, \eta^{[1]}, \ldots, \eta^{[t-1]}, x^{[t]}\right\}$ indicates the corresponding information set. For clarity of presentation, we solve for an optimal $d^{[t]}$ in an arbitrary period t. In addition, we drop the superscript for γ and ε to focus on the intertemporal variability solely in market price (Table 1).

Notice that in period t, $d^{[t+1]}, \ldots, d^{[L]}$ will be anticipated future optimal quantities based on the current information set $X^{[t]}$, whereas $d^{[1]}, \ldots, d^{[t-1]}$ will be previous decisions realized to the storage. To avoid confusion, we denote their solutions by a general $\mathbb{E}_t d^{[\tau]}, \tau = 1, \ldots, L$. Under this notation, $\mathbb{E}_t d^{[\tau]}, \tau = 1, \ldots, t-1$ will be known data, $\mathbb{E}_t d^{[t]}$ is the decision to be made in period t, and $\mathbb{E}_t d^{[\tau]}, \tau = t+1, \ldots, L$ will be the anticipated future optimal quantities. It should be emphasized that $\mathbb{E}_t d^{[\tau]}$ may not be the same as the actual decision made in a future period τ, for $\tau = t+1, \ldots, L$. The timeline in this model is shown in Fig. 1.

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[2] It is noted that, we study battery energy storage with advanced technologies such as Li-on based. This kind of energy storage is of very high efficiency and the modeling error using a cost function to capture the energy loss during charging/discharging is negligible, and thus ignored in our abstraction. However, it is possible to include the

Table 1
Summary of nomenclature.

I	The set of energy storages, $|I| = n$.
J	The set of targeted information release recipients, $|J| = m$.
T	The set of time periods, $|T| = L$.
$X_i^{[t]}$	Information set of storage i in period t.
A	Equilibrium base storage quantity.
C	Equilibrium response factors with respect to private forecasts.
B	Equilibrium response factor towards the public forecast.
$d_i^{[t]}$	The amount of energy purchased or sold by the ith storage at time t.
$D^{[t]}$	The aggregate storage quantity $D^{[t]} = \sum_{i=1}^{i=n} d_i^{[t]}$.
$P^{[t]}$	Market clearing energy price at time t.
$x_i^{[t]}$	Private forecast received by storage i regarding market uncertainty.
$x_0^{[t]}$	Public forecast.
$\eta^{[t]}$	Market price uncertainty at time t.
$\beta^{[t]}$	Market potential.
$\gamma^{[t]}$	Energy price elasticity.
α	Information precision for market uncertainty $a\ priori$.
δ	Autoregression parameter for market uncertainty.
ϵ_t	Exogeneous price shock at time t.
ζ	Precision of ϵ_t.
$\varepsilon^{[t]}$	Quadratic energy storage cost coefficient.
ρ	Precision of the private forecast $x_i^{[t]}$.
π_i	Storage i's payoff function.
σ	Precision of the public forecast $\xi_0^{[t]}$.
$\xi_i^{[t]}$	Noise of the private information channel by storage i.
$\xi_0^{[t]}$	Noise of the public information channel.

Fig. 1. Timeline of the centralized storage model.

By the *Principal of Optimality*, in period t, we use the following induced sub-problem to find $\mathbb{E}_t d^{[t]}$ (optimal solution of $d^{[t]}$):

$$\max_{d^{[t]}, d^{[t+1]}, \dots, d^{[L]}} \sum_{\tau=t}^{\tau=L} \mathbb{E}\left[\left(\beta^{[\tau]} - \gamma d^{[\tau]} + \eta^{[\tau]} \right) d^{[\tau]} - \varepsilon \cdot \left(d^{[\tau]} \right)^2 | X^{[t]} \right],$$

subject to

$$\mathbb{E}\left[\sum_{\tau=t}^{\tau=L} d^{[\tau]} | X^{[t]} \right] = -\sum_{\tau=1}^{\tau=t-1} d^{[\tau]}. \tag{5}$$

Proposition 1. *The optimal storage quantity in period t is denoted by*

$$\mathbb{E}_t d^{[t]} = \underbrace{\frac{\beta^{[t]} - \frac{\sum_{\tau=t}^{\tau=L} \beta^{[\tau]}}{L-t+1}}{2(\varepsilon+\gamma)} - \frac{\sum_{\tau=1}^{\tau=t-1} d^{[\tau]}}{L-t+1}}_{\text{base storage quantity}} + \underbrace{\frac{\left(1 - \frac{\sum_{\tau=t}^{\tau=L} \delta^{\tau-t}}{L-t+1} \right)}{2(\varepsilon+\gamma)}}_{\text{response factor}} \cdot \mathbb{E}\left[\eta^{[t]} | X^{[t]} \right], \tag{6}$$

for $t = 1, 2, \dots, L-1$, wherein $\mathbb{E}\left[\eta^{[t]} | X^{[t]} \right] = \frac{\rho}{\rho+\zeta} x^{[t]} + \frac{\zeta\delta}{\rho+\zeta} \eta^{[t-1]}$, for $t = 2, \dots, L$, and $\mathbb{E}\left[\eta^{[1]} | X^{[1]} \right] = \frac{\rho}{\rho+\alpha} x^{[1]}$. In the final period, $\mathbb{E}_L d^{[L]} = -\sum_{\tau=1}^{\tau=L-1} d^{[\tau]}$.

physical process of energy loss by modeling the charging/discharging process of energy storage, which will complicate the main finding rather than affecting the main conclusions of this work.

In this proposition, we are able to derive the optimal storage quantities in closed form, comprising of two parts: The first part is the *base storage quantity*, and the second part is the *response factor* multiplied by an estimation of the market price uncertainty. The base storage quantity decreases in ε (cost coefficients with respect to the depth of discharge) and γ (energy price elasticity). The market price uncertainty is estimated by a convex combination of a current forecast and a last-period observation: $\mathbb{E}\left[\eta^{[t]}|X^{[t]}\right] = \frac{\rho}{\rho+\zeta}x^{[t]} + \frac{\zeta\delta}{\rho+\zeta}\eta^{[t-1]}$. The weighting factors are proportional to their relative precision levels ρ and ζ. In additional, the last-period observation weights more when the intertemporal correlation is stronger (δ is higher).

From this proposition, we can clearly see that the optimal storage quantities depend on both variability (captured by market potential coefficient $\beta^{[t]}$) and uncertainty (captured by $\eta^{[t]}$) in market price. The base storage quantity demonstrates a downward distortion to the per-stage optimal storage quantity $\frac{\beta^{[t]}}{2(\varepsilon+\gamma)}$: The component $\sum_{\tau=t}^{\tau=L}\frac{\beta^{[\tau]}}{L-t+1}\frac{1}{2(\varepsilon+\gamma)}$ is the average per-stage optimal storage quantity across all future periods, and the component $\sum_{\tau=1}^{\tau=t-1}\frac{d^{[\tau]}}{L-t+1}$ is subtracted to compensate the existing energy storage level built up in the past. The downward distortion ensures that the overall storage quantities offset each other, i.e., $\mathbb{E}\left[\sum_{t\in T}d^{[t]}|X^{[t]}\right] = 0$.

4.2. Stylized solution of multiple storages in two-period

In this section, we recover the superscript for γ and ε. We also recover the subscript for $x_i^{[t]}$ since the storages observe heterogeneous information. To characterize the equilibrium outcome under such highly asymmetric information structure, we first introduce our solution concept.

Equilibrium concept. Storage i chooses a storage quantity $d_i^{[1]}$ to maximize $\mathbb{E}[\pi_i|x_i^{[1]}]$, by forming an expectation of the other producers' production levels $\mathbb{E}(d_j^{[1]}|x_i^{[1]})$, for $\forall j \neq i$. $d_i^{[2]}$ is determined thereafter, due to the constraint $d_i^{[1]} + d_i^{[2]} = 0$, $\forall i \in I$. We focus exclusively on the *linear symmetric Bayesian–Nash equilibrium*, i.e., $d_i^{[1]} = A + Cx_i^{[1]}$, for some constants A and C. We can interpret A as the *base storage quantity*; C as the *response factors* with respect to the forecast $x_i^{[1]}$, respectively.

Proposition 2. *For a two-period model under private market forecasting, the storage quantity in the linear symmetric Bayesian-Nash equilibrium is $d_i^{[1]} = A + Cx_i^{[1]}$ for every storage, wherein*

$$A = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)},$$

$$C = \frac{(1-\delta)\rho}{\left[(n-1)\left(\gamma^{[1]} + \gamma^{[2]}\right)\rho + 2\left(\varepsilon^{[1]} + \varepsilon^{[2]} + \gamma^{[1]} + \gamma^{[2]}\right)(\alpha+\rho)\right]}.$$

In period $t=1$, the base storage quantity A is positive (selling energy) if and only if $\beta^{[1]} > \beta^{[2]}$, i.e., the energy price decreases at $t=2$. Conversely, the storage buys energy ($A<0$) when it can be sold at a higher price at $t=2$ ($\beta^{[1]} < \beta^{[2]}$). Consistent with our results in the single storage model, the base selling quantity decreases in $\sum_{t\in T}\varepsilon^{[t]}$ (cost coefficients with respect to the depth of discharge), and in $\sum_{t\in T}\gamma^{[t]}$ (aggregate energy price elasticity). Furthermore, when $A>0$, it decreases in the number of storages. This is because that the market competition is more intense as the number of Cournot competitors increases, and consequently, the price of energy decreases. The converse is true when $A<0$.

The reaction to private forecast C is more aggressive when its precision ρ increases, as a storage relies more on an accurate market forecast. The reactions to forecasts are less aggressive when the intertemporal correlation δ increases. In the extreme case where $\delta=1$, the storage does not respond to forecasts. Intuitively, this is because that any action (either buy or sell) in response to a market forecasts at $t=1$ will be offset by a reverse operation (under the energy balance constraints $\sum_{t\in T}d_i^{[t]} = 0$) at $t=2$ when the market condition remains the same.

Proposition 3. *When there are a large number of storages, every storage's equilibrium payoff converges asymptotically to*

$$\lim_{n\to\infty}\mathbb{E}[\pi_i] \to \sum_{t=1,2}\left(\varepsilon^{[t]} + \gamma^{[t]}\right)\left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}}\right)^2\rho^{-1}\right]\cdot n^{-2}. \tag{7}$$

When there are a large number of storages, $\lim_{n\to\infty}\mathbb{E}[\pi_i]$ decreases in ρ. This result demonstrates the negative economic value of a private forecast, and is interpreted as *competition effect*. Although storages' private forecasts are independent, they lead to similar reaction to a market price shock. When the number of storages is large, the purchase or selling quantity responses are exaggerated and the over-precision in forecasts can lead to even lower payoffs. The inverse-square decay with respect to the number of storages demonstrates the impact of competition intensity.

We complement the analysis with the following numerical example, wherein $\beta^{[1]} - \beta^{[2]} = 1$, $\varepsilon^{[1]} = \varepsilon^{[2]} = \gamma^{[1]} = \gamma^{[2]} = 1$, and the payoff is calculated with a finite number of storages. We summarize the results in Fig. 2. Note that throughout the entire paper, the vertical scales in all figures are erased to focus on trends instead of absolute value.

A storage's payoff decreases in the autoregressive parameter δ. As a storage's reactions to forecasts are less responsive when the intertemporal correlation (δ) increases, the economic value of market information also decreases. For a similar reason, a storage's payoff also decreases in market uncertainty parameter α, as the storage's reactions to forecasts are also less responsive in this case. In addition, the inverse-square decay with respect to the number of storages confirms our result in the asymptotic analysis. Finally, a storage's payoff first increases then decreases in its private information precision. When private information is scarce, the economic value of private information
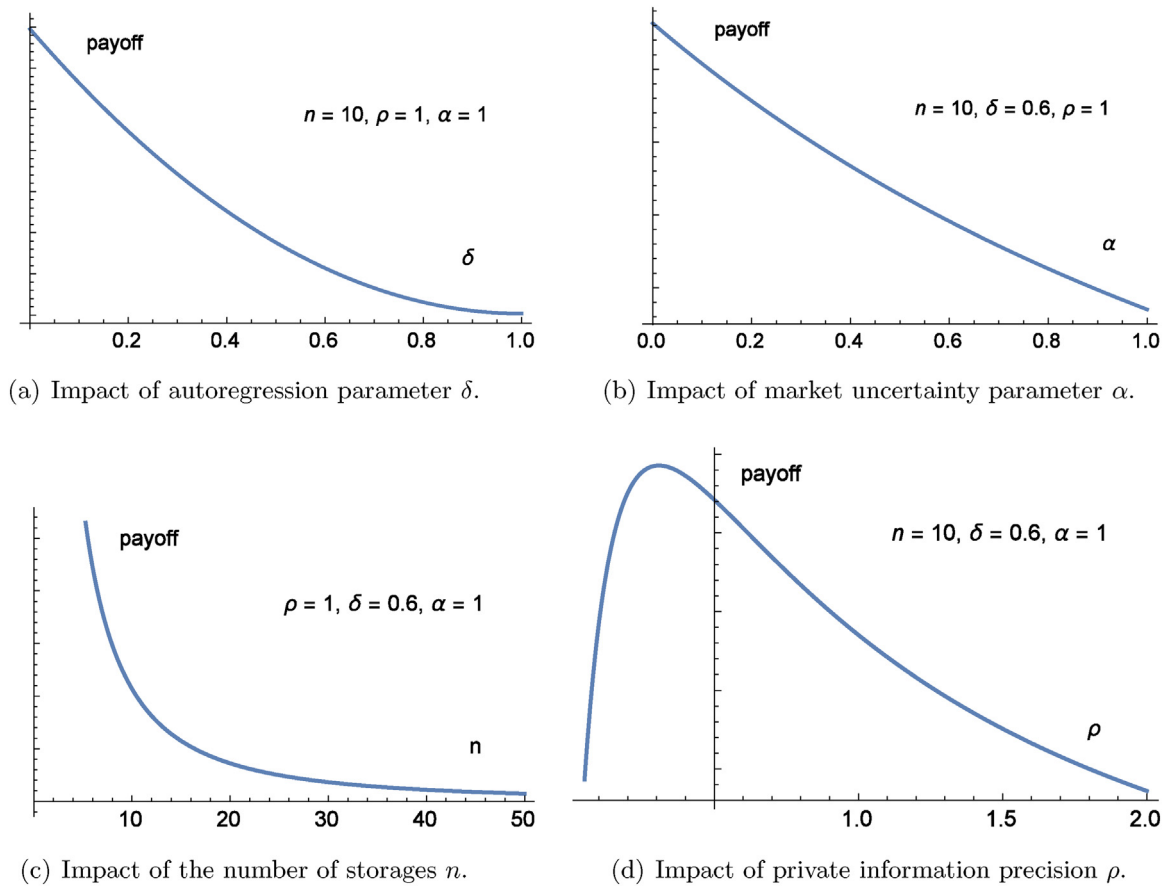
(a) Impact of autoregression parameter δ.

(b) Impact of market uncertainty parameter α.

(c) Impact of the number of storages n.

(d) Impact of private information precision ρ.

Fig. 2. Sensitivity analysis of individual storage's payoff with respect to model primitives.

increases in its precision as it mitigates uncertainty. However, when the information precision further increases, the competition effect dominates and the payoff decreases.

5. Operational policy analysis

5.1. Public forecast provision

Suppose that instead of private forecasts, all the storages receive a public forecast $x_0^{[t]} = \eta^{[t]} + \xi_0^{[t]}$, where $\xi_0^{[t]} \sim N(0, \sigma^{-1})$. In this section, we analyze the possibility for a public forecast to coordinate storages' actions. This can be potentially provided by the aggregator. Following a similar analysis as in the private forecasting model, we assume that $d_i^{[1]} = A + Bx_0^{[1]}$, where B is the response factor towards the public forecast.

Proposition 4.   *For a two-period model under public market forecasting, each storage's equilibrium storage quantity in the linear symmetric Bayesian–Nash equilibrium is $d_i^{[1]} = A + Bx_0^{[1]}$, wherein*

$$A = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)},$$

$$B = \frac{(1-\delta)\sigma/(\alpha+\sigma)}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)}.$$

The equilibrium payoff

$$\lim_{n\to\infty} \mathbb{E}[\pi_i] \to \sum_{t=1,2} \left(\varepsilon^{[t]} + \gamma^{[t]}\right) \left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 \cdot \frac{\sigma}{(\alpha+\sigma)^2}\right] \cdot n^{-2}.$$

Similar to the private forecasting model, the reaction to public forecast B is more aggressive when its precision σ increases. $\lim_{n\to\infty} \mathbb{E}[\pi_i]$ is pseudo-concave in the public forecast precision σ, and thus reaches the global maximum when $\sigma = \alpha$. Notice that, when $\sigma > \alpha$, $\lim_{n\to\infty} \mathbb{E}[\pi_i]$ decreases in σ, which demonstrate the negative economic value of a public forecast. We interpret this as *congestion effect*: Intuitively, when $\sigma > \alpha$, over-reaction to a public forecast leads to either too much purchase quantity (when forecast is favorable) or too much selling quantity
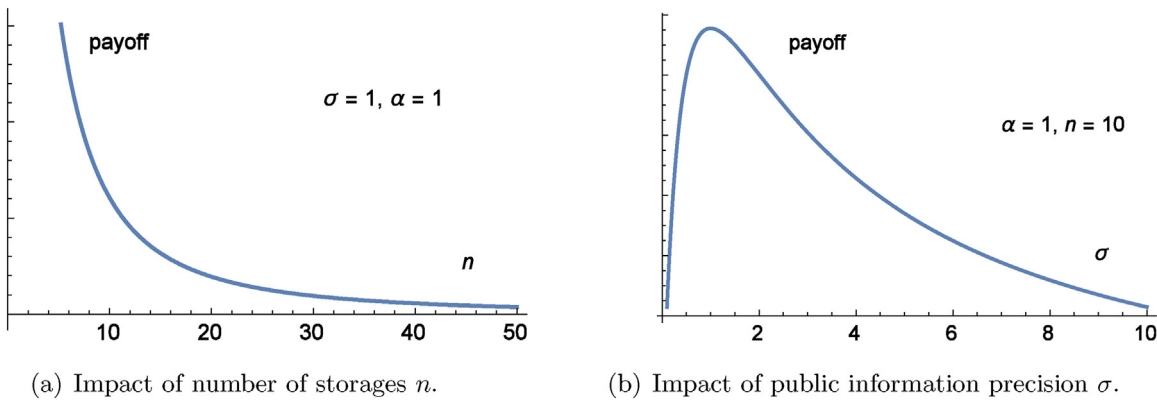
(a) Impact of number of storages n.

(b) Impact of public information precision σ.

Fig. 3. Sensitivity analysis of individual storage's payoff under public information provision.

(unfavorable forecast) from all storages. The public forecast becomes a herding signal. It is beneficial to maintain certain exclusiveness of a public forecast. For given information provision, a storage's payoff suffers inverse-square decay in the number of storages, as the economic value of a public forecast is diluted when more storages respond to it.

We complement the analysis with the following numerical example summarized in Fig. 3, wherein $\beta^{[1]} - \beta^{[2]} = 1$, $\varepsilon^{[1]} = \varepsilon^{[2]} = \gamma^{[1]} = \gamma^{[2]} = 1$, and the payoff is calculated with a finite number of storages. Again, a storage's payoff decreases to the inverse-square of the number of storages as shown in the analytical result. A storage's payoff first increases (due to positive economic value) then decreases (due to the congestion effect) in the precision of the public market forecast.

5.2. Encourage information sharing

Suppose that the storages pool their private forecasts $x_i^{[1]}$ together. In this case, it can be checked that it is equivalent for them to observe a public forecast $x_0^{[1]}$ with precision $\sigma = n\rho$:

$$\mathbb{E}[\eta^{[1]}|x_1^{[1]}, \ldots, x_n^{[1]}] = \frac{\rho}{\alpha + n\rho} \sum_{i \in I} x_i^{[1]}, \ \mathbb{E}[\eta^{[1]}|x_0^{[1]}] = \frac{\sigma}{\alpha + \sigma} x_0^{[1]},$$

and it can be checked that these two estimators are stochastically equivalent, i.e., both $N(0, \frac{n\rho}{(\alpha+n\rho)^2})$. Intuitively, when the private storages pool their signals together, the collected signal will be equivalent to a public one; thus, by evaluation the extreme cases of complete information sharing with private forecasts, we will receive the same conclusion in terms of the payoffs between public and private forecasts.

Therefore, we can calculate the corresponding payoffs under pooled private forecasts:

$$\lim_{n \to \infty} \mathbb{E}[\pi_i; \sigma = n\rho] \to \sum_{t=1,2} \left(\varepsilon^{[t]} + \gamma^{[t]}\right) \cdot \left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 \cdot (n\rho)^{-1} \right] \cdot n^{-2}$$

$$< \sum_{t=1,2} \left(\varepsilon^{[t]} + \gamma^{[t]}\right) \left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 \rho^{-1} \right] \cdot n^{-2}.$$

By comparing this payoff with that under private forecasts, we find that the economic value of forecast under information sharing is (to an order of magnitude in the number of storages) lower than that under private forecasts. There will be no incentive for the storage to share information with each other. From this analysis, we find that communication among the storages fails to achieve a coordinated effort to increase market efficiency. To maintain the exclusiveness of their private forecasts, the decentralized storages should not be encouraged to share market information in this regime. This result is confirmed by a numerical analysis summarized in Fig. 4 when there are a large number of storages. However, when the number of storages is small, it is possible that every storage is better off by information sharing. This regime is possible when each private forecast is extremely fuzzy, and pooling them together can amplify the market signal.

5.3. Targeted information release

Now that we know the exclusiveness of a market forecast is important, we analyze an alternative policy intervention through public information channel. Suppose that the aggregator/government offers a public forecast only to a subset of storages J ($|J| = m \leq n$). For informed storages (ones who receive the public forecast), their $d_i^{[1]} = A + Bx_0^{[1]}$, $\forall i \in J$. For uninformed storages, their $d_i^{[1]} = C$, $\forall i \in I - J$. A, B and C are all unknown constant coefficients.

Informational intervention is possible through recent technology such as "smart energy storage", which refers to a system wherein the batteries charge at night and release electricity at peak times during the day to shave load. In this context, the "informed storages" correspond to the smart storage while the uninformed storages correspond to the regular ones, which either do not have access to the market data or do not utilize it for load-shaving.
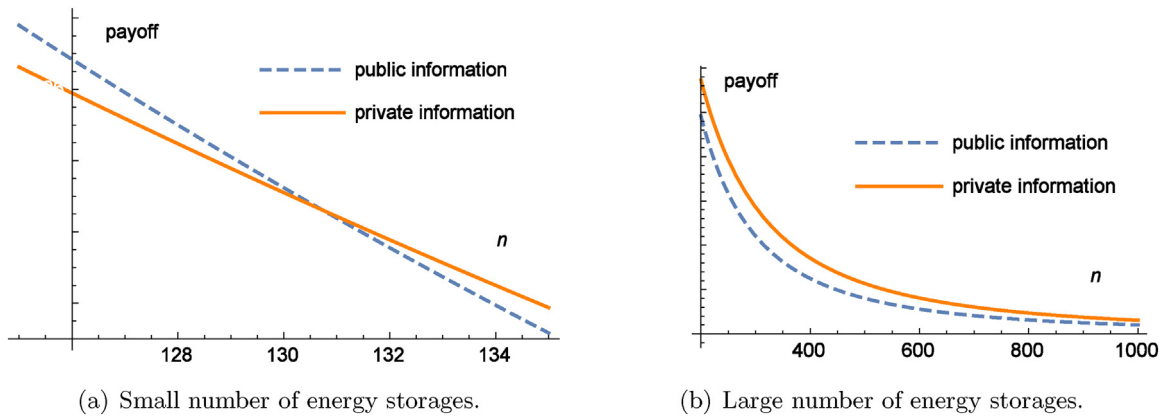
(a) Small number of energy storages.　　　　(b) Large number of energy storages.

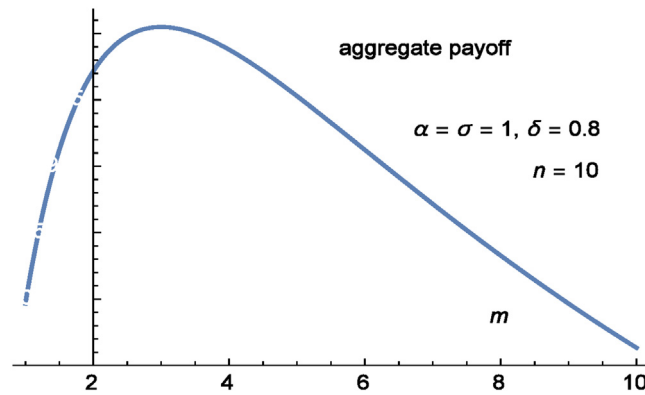**Fig. 4.** Individual payoff comparison with and without information sharing.

Fig. 5. Storages' aggregate payoff changes in the number of information recipient. Note that it is optimal to target only a subset of recipients.

Proposition 5. *For a two-period model under targeted information release, storages' equilibrium storage quantities in the linear Bayesian–Nash equilibrium are $d_i^{[1]} = A + B x_0^{[1]}, \forall i \in J$, and $d_i^{[1]} = C, \forall i \in I - J$, wherein*

$$A = C = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)},$$

$$B = \frac{(1-\delta)\sigma/(\alpha+\sigma)}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (m+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)}.$$

The storages' aggregate payoff $\sum_{i \in I} \mathbb{E}[\pi_i]$ is maximized when the population of information recipient

$$m = 1 + \frac{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right)}{\gamma^{[1]} + \gamma^{[2]}}. \tag{8}$$

In this case, the storages' payoffs are stratified, due to their asymmetrical informational status. The fact that an interior solution (in Fig. 5 the optimal number of recipients is 3) exists suggests a trade-off between the economic value of a public forecast in coordinating the storages' actions, and the congestion effect due to the lack of exclusiveness of such information dissemination. We can show the following trends asymptotically: since the public information provision is a special case to the targeted information release (wherein the target set being the whole population), thus, the public information provision leads to a lower aggregate payoff than that under the targeted information releases; we do not compare the aggregated payoff under targeted information release with that under private forecasts, due to the complexity in obtaining the exact payoff formula in this case. When it is difficult to directly dictate the energy controls, a policy-maker can indirectly improve social welfare by informational instrument, which is in line with Zhou and Chen (2016) from the literature. Applications of such a policy have been observed via targeted mobile apps/messages (Zhou and Chen, 2016). With the smart-meters technology, it is possible to achieve informational control for energy storage systems. In the context of "smart energy storages", our results then suggest, somewhat surprisingly, it is not necessarily better for all energy storages to be "smart", even if we ignore their technology costs; it is optimal to select some but not all storages to be smart.
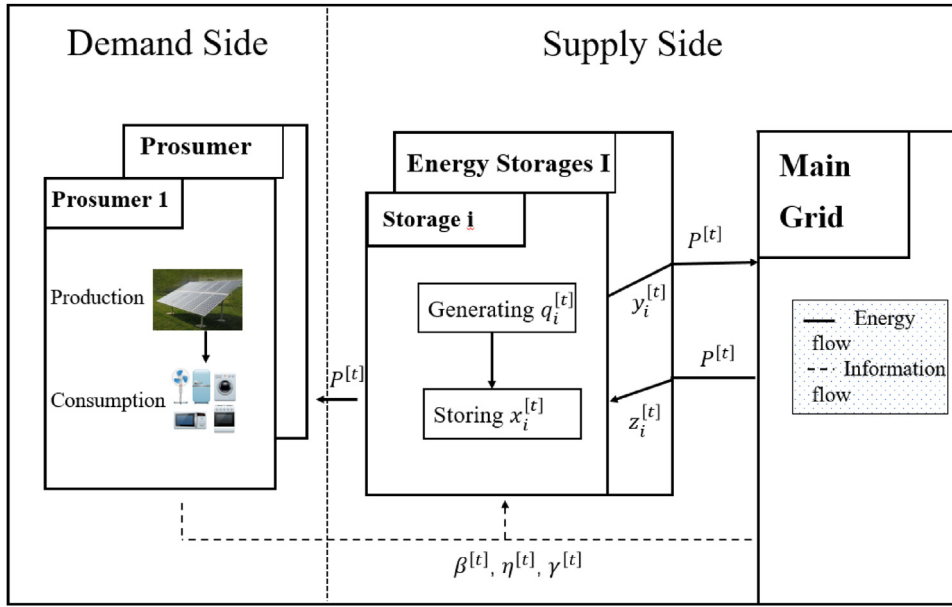
Fig. 6. System configuration for the generalized model.

6. Model generalizations

6.1. The prosumer model

To further justify the model setup with the context of energy storage, we had considered a generalized model wherein we integrate the power generation and consumption with the storage component. Consider n energy "prosumer", which we will define as the integrated agents who generate, store and consume energy (she) connected through a common market (we abstract away from the actual energy transmissions and transactions). The prosumers indexed by a set $N = \{1, 2, \ldots, n\}$, for simplicity, are homogeneous *ex ante*. Throughout this extension, we consider two periods and index time by $t = 1, 2$. The prosumer, with excessive energy not stored, is able to sell energy back to the grid in accordance with trade-in tariff agreement.

Let $q_i^{[t]}$ denote the energy quantity generated from the ith prosumer at time t, whereas she stores $x_i^{[t]}$ amount of energy in her energy storage during the same period. If $x_i^{[t]} \geq q_i^{[t]}$, the household purchases the remaining energy $z_i^{[t]} = x_i^{[t]} - q_i^{[t]}$ from the market. If $x_i^{[t]} < q_i^{[t]}$, the prosumer sells the extra energy $y_i^{[t]} = q_i^{[t]} - x_i^{[t]}$ to the market. Therefore, we define the buying and selling quantities as

$$z_i^{[t]} = \left(x_i^{[t]} - q_i^{[t]} \right)^+, y_i^{[t]} = \left(q_i^{[t]} - x_i^{[t]} \right)^+, \quad \forall i \in N, \quad \forall t = 1, 2. \tag{9}$$

We also assume that $q_i^{[t]} = q^{[t]}$ for $\forall t = 1, 2, \forall i \in N$, to focus on symmetric equilibrium such that the generators are homogeneous *ex ante*.

Similar to the basic model in the main manuscript, we model the market structure by assuming that the market clearing electricity price $P^{[t]}$ is linearly decreasing in the net aggregate energy supply, i.e.,

$$P^{[t]} = \beta^{[t]} - \varepsilon^{[t]} \left(\sum_{\forall i \in N} y_i^{[t]} - \sum_{\forall i \in N} z_i^{[t]} \right), \quad \forall t = 1, 2. \tag{10}$$

$\beta^{[t]} > 0$ corresponds to a baseline price driven by traditional energy supply. $\beta^{[t]}$ can also capture market variability since it is changing over time. $\varepsilon^{[t]} > 0$ captures the decrease of market price in the aggregate market supply of energy (Fig. 6).

Without loss of generality, we assume that the first-period is buying period while the second period is the selling period. Then, rewriting $d_i^{[1]} = x_i^{[1]} = -x_i^{[2]}$, it can be checked that the payoff function is of second-order with respect to the storage amount, which is consistent with the basic model.

6.2. Multi-period model

In this section, we demonstrate that the model can be extended in multiple directions. A multi-period version of this problem has to be solved recursively using backward induction while unfolding the information set throughout the process. Instead, we analyze a relaxed problem. In this case, equilibrium characterization requires solving the following optimization problems:

$$\max_{d_i^{[t]}, t \in T} \sum_{t \in T} \mathbb{E} \left[P^{[t]}(D^{[t]}) \cdot d_i^{[t]} - \varepsilon^{[t]} \cdot \left(d_i^{[t]} \right)^2 | X_i^{[t]} \right],$$

subject to

$$\mathbb{E}\left[\sum_{t \in T} d_i^{[t]}\right] = 0. \tag{11}$$

$X_i^{[t]} = \left\{ x_0^{[1]}, x_i^{[1]}, \eta^{[1]}, \ldots, \eta^{[t-1]}, x_0^{[t]}, x_i^{[t]} \right\}$ indicates the corresponding information set. Notice that we simultaneous incorporate private forecasts $\{x_i^{[t]}\}$'s and a public forecast $x_0^{[t]}$. The storage quantity will be $d_i^{[t]} = A^{[t]} + B^{[t]}x_0^{[t]} + C^{[t]}x_i^{[t]}$ for some unknown coefficients $A^{[t]}$, $B^{[t]}$ and $C^{[t]}$. This is a relaxation because an exact solution requires that $\mathbb{E}\left[\sum_{t \in T} \left(d_i^{[t]}\right)^* | X_i^{[t]}\right] = 0$, for any sample path generated by $\{X_i^{[t]}\}$'s.

Proposition 6. *For a multi-period model under both private and public market forecasting, the storage quantities in the linear symmetric Bayesian-Nash equilibrium can be approximated by $d_i^{[t]} = A^{[t]} + B^{[t]}x_0^{[t]} + C^{[t]}x_i^{[t]}$, wherein*

$$A^{[t]} = \frac{\beta^{[t]} - \lambda}{2\varepsilon^{[t]} + (n+1)\gamma^{[t]}},$$

$$C^{[t]} = \frac{\rho}{\left[2\left(\varepsilon^{[t]} + \gamma^{[t]}\right)(\alpha + \sigma + \rho) + (n-1)\gamma^{[t]}\rho\right]},$$

$$B^{[t]} = \frac{\sigma - (n-1)\gamma^{[t]}\sigma C}{\left[(n+1)\gamma^{[t]} + 2\varepsilon^{[t]}\right](\alpha + \sigma + \rho)},$$

and the Lagrangian multiplier

$$\lambda = \frac{\sum_{t \in T} \beta^{[t]} \prod_{\tau \neq t} \left[2\varepsilon^{[\tau]} + (n+1)\gamma^{[\tau]}\right]}{\sum_{t \in T} \prod_{\tau \neq t} \left[2\varepsilon^{[\tau]} + (n+1)\gamma^{[\tau]}\right]}. \tag{12}$$

The downside of this analysis is that we cannot guarantee that $\mathbb{E}\left[\sum_{t \in T} \left(d_i^{[t]}\right)^* | X_i^{[t]}\right] = 0$. Essentially, the storages reduce the baseline quantity $A^{[t]}$ by their time-average so that the aggregate buy/sell quantities sum up to zero in the statistical sense. This approximation of the storages' actions ignores the intertemporal correlation of uncertainties. Future research is needed for an exact analysis of the full-fledged model.

6.3. Heterogeneous storages

We model storages with heterogeneous physical attributes and information status by assuming that the costs of utilizing storage $c_i(d) = \varepsilon_i^{[t]} \cdot d^2$, and storage i receives a private forecast $x_i^{[t]}$ with precision ρ_i. To illustrate the major points, we extend the two-period model.

Proposition 7. *For a two-period model under both private and public market forecasting, the heterogeneous storage quantities in the linear Bayesian–Nash equilibrium take the form of $d_i^{[1]} = A_i + B_i x_0^{[1]} + C_i x_i^{[1]}$, wherein A_i, B_i, and C_i are given in Appendix A.*

As in the basic model with homogeneous storages, each storage holds its own forecast but with varying precision:

$$\mathbb{E}[\eta^{[1]}|x_0^{[1]}, x_i^{[1]}] = \frac{\sigma}{\alpha + \sigma + \rho}x_0^{[1]} + \frac{\rho_i}{\alpha + \sigma + \rho_i}x_i^{[1]}. \tag{13}$$

The interesting new feature in this extension is that each storage (i) needs to guess another storage's (j) quantity decision via its own information set:

$$\mathbb{E}[d_j^{[1]}|x_0^{[1]}, x_i^{[1]}] = A_j + B_j x_0^{[1]} + C_j \mathbb{E}[x_j^{[1]}|x_0^{[1]}, x_i^{[1]}]. \tag{14}$$

To obtain a correct conjecture, storage i needs to estimate storage j's private forecast:

$$\mathbb{E}[x_j^{[1]}|x_0^{[1]}, x_i^{[1]}] = \mathbb{E}[\eta^{[1]} + \xi_j^{[1]}|x_0^{[1]}, x_i^{[1]}] = \mathbb{E}[\eta^{[1]}|x_0^{[1]}, x_i^{[1]}]. \tag{15}$$

Following a similar procedure as in the basic homogeneous model, we can obtain the coefficients summarized in Appendix A. The dependency of the value of both public and private forecasts on their precisions σ and ρ_i is highly nonlinear. Due to the complicated payoff functional forms of this general model, we start with the homogeneous model for a clear presentation of results. It can be checked that some of our findings and intuitions remain robust under this generalization. For example, the base storage quantity A is positive (selling energy) if and only if $\beta^{[1]} > \beta^{[2]}$, i.e., the energy price decreases at $t=2$. The value of a private forecast ($C_i^2 \mathbb{E}[x_i^{[1]}]^2$) is proportional to $\left[\frac{(1-\delta)}{\alpha + \sigma + \rho_i}\right]^2 \rho_i$, and thus decreasing in the intertemporal correlation δ, as the reactions to forecasts are less aggressive when δ increases.

7. Conclusion

In this paper, we propose stylized models of decentralized energy storage operation under private and public market forecasting, when energy prices are both uncertain and variable over time. We derive the optimal buying or selling quantities for storages in a competitive environment with strategic interactions. Coarsely speaking, a foresighted storage will plan to buy energy when its price is low and sell when the price high. The value of a private forecast decreases in the intertemporal correlation of market price shock. We demonstrate the potentially negative economic value of a private forecast, due to *competition effect*: When there are a large number of storages, the purchase or selling quantity responses are exaggerated and the over-precision in forecasts can lead to even lower payoffs. These fundamental observations are robust when we generalize the model to multi-period or heterogeneous storages.

We also examine several information management policies to coordinate storages' actions and improve their profitability. Firstly, we demonstrate the potential negative economic value of a public forecast, due to *congestion effect*: A precise public forecast leads to herding behavior, and over-reaction to a public forecast leads to either too much purchase quantity (when forecast is favorable) or too much selling quantity (unfavorable forecast) from all storages. Secondly, we find that communication among the storages could fail to achieve a coordinated effort to increase market efficiency. The decentralized storages will not participate in any information sharing program when there are a large number of storages. Thirdly, we find it optimal to release additional information to a subset of energy storages exclusively by targeted information release.

Future research is needed for a full-fledged analysis of a multi-period, decentralized, and heterogeneous model. In the basic model, a storage's payoff decreases in the auto-regressive parameter. Thus, the payoff is lower when the market is more correlated inter-temporally, since the storage's reactions to forecasts are less responsive. Conversely, the information value will be higher when the inter-temporal shocks are negatively correlated (when δ is negative). Future studies will be interesting to investigate the diurnal cycle in further detail. Another direction to go is to incorporate operational constraints such as energy and/or power limits. Explicit modeling of renewable energy generation will contribute to a holistic understanding of the entire integrated system. Finally, information management research in other energy markets is likely to be promising.

Appendix A. Proofs

A.1 Proof of Proposition 1

Introduce a Lagrangian multiplier $\lambda^{[t]}$ to relax the conservation constraint. We denote the Lagrangian by

$$
L = \sum_{\tau=t}^{\tau=L} l^{[\tau]} = \sum_{\tau=t}^{\tau=L} \mathbb{E} \left[\begin{array}{c} \left(\beta^{[\tau]} - \gamma d^{[\tau]} + \eta^{[\tau]} \right) d^{[\tau]} \\ -\varepsilon \cdot \left(d^{[\tau]} \right)^2 - \lambda^{[t]} d^{[\tau]} \end{array} \middle| X^{[t]} \right] - \lambda^{[t]} \sum_{\tau=1}^{\tau=t-1} d^{[\tau]}
$$

By the first-order condition $\frac{\partial l^{[\tau]}}{\partial d^{[\tau]}} = 0$, for $\tau = t, \ldots, L \Rightarrow$

$$
\mathbb{E}_t d^{[\tau]} = \frac{\beta^{[\tau]} - \lambda^{[t]} + \mathbb{E} \left[\eta^{[\tau]} | X^{[t]} \right]}{2 (\varepsilon + \gamma)}. \tag{16}
$$

Notice that $\mathbb{E} \left[\eta^{[\tau]} | X^{[t]} \right] = \delta^{\tau-t} \mathbb{E} \left[\eta^{[t]} | X^{[t]} \right]$, for $\tau = t, \ldots, L$, and $\mathbb{E} \left[\sum_{\tau=t}^{\tau=L} d^{[\tau]} | X^{[t]} \right] = -\sum_{\tau=1}^{\tau=t-1} d^{[\tau]} \Rightarrow$

$$
\lambda^{[t]} = \frac{\sum_{\tau=t}^{\tau=L} \beta^{[\tau]} + \sum_{\tau=t}^{\tau=L} \delta^{\tau-t} \mathbb{E} \left[\eta^{[t]} | X^{[t]} \right] + 2 (\varepsilon + \gamma) \sum_{\tau=1}^{\tau=t-1} d^{[\tau]}}{L - t + 1} \tag{17}
$$

Therefore,

$$
\mathbb{E}_t d^{[t]} = \frac{\beta^{[t]} - \frac{\sum_{\tau=t}^{\tau=L} \beta^{[\tau]}}{L-t+1}}{2 (\varepsilon + \gamma)} + \frac{\left(1 - \frac{\sum_{\tau=t}^{\tau=L} \delta^{\tau-t}}{L-t+1} \right) \mathbb{E} \left[\eta^{[t]} | X^{[t]} \right]}{2 (\varepsilon + \gamma)} - \frac{\sum_{\tau=1}^{\tau=t-1} d^{[\tau]}}{L - t + 1}. \tag{18}
$$

$\square$

A.2 Proof of Proposition 2

The payoff can be simplified by plugging $d_i^{[2]} = -d_i^{[1]}$. To derive the equilibrium storage quantities, we set $\frac{\partial \mathbb{E}[\pi_i | x_i^{[1]}]}{\partial d_i^{[1]}} = 0$:

$$
\left[\begin{array}{c} \beta^{[1]} - \beta^{[2]} - \left(\gamma^{[1]} + \gamma^{[2]} \right) \sum_{j \neq i} \mathbb{E}[d_j^{[1]} | x_i^{[1]}] \\ + \mathbb{E}[\eta^{[1]} | x_i^{[1]}] - \mathbb{E}[\eta^{[2]} | x_i^{[1]}] - 2 \left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon^{[1]} + \varepsilon^{[2]} \right) \cdot d_i^{[1]} \end{array} \right] = 0. \tag{19}
$$

Notice that

$$
\mathbb{E}[d_j^{[1]} | x_i^{[1]}] = A + B x_0^{[1]} + C \mathbb{E}[x_j^{[1]} |, x_i^{[1]}],
$$

$$
\mathbb{E}[x_j^{[1]} | x_i^{[1]}] = \mathbb{E}[\eta^{[1]} + \xi_j^{[1]} | x_i^{[1]}] = \mathbb{E}[\eta^{[1]} | x_i^{[1]}],
$$

$$\mathbb{E}[\eta^{[2]}|x_i^{[1]}] = \mathbb{E}[\delta\eta^{[1]} + \epsilon_1|x_i^{[1]}] = \delta\mathbb{E}[\eta^{[1]}|x_i^{[1]}],$$

$$\mathbb{E}[\eta^{[1]}|x_i^{[1]}] = \frac{\rho}{\alpha+\rho}x_i^{[1]}.$$

By matching the coefficients with respect to $x_i^{[1]}$, we have

$$A = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)},$$

$$C = \frac{(1-\delta)\rho}{\left[\begin{array}{c}(n-1)\left(\gamma^{[1]} + \gamma^{[2]}\right)\rho + \\ 2\left(\varepsilon^{[1]} + \varepsilon^{[2]} + \gamma^{[1]} + \gamma^{[2]}\right)(\alpha+\rho)\end{array}\right]}.$$

□

A.3 Proof of Proposition 3

The payoff can be calculated through

$$\begin{aligned}\mathbb{E}[\pi_i] &= \mathbb{E}\left[\mathbb{E}[\pi_i|x_i^{[1]}]\right]\\ &= \left(\varepsilon^{[1]} + \varepsilon^{[2]} + \gamma^{[1]} + \gamma^{[2]}\right)\left(A^2 + C^2\mathbb{E}[x_i^{[1]}]^2\right).\end{aligned}$$

Notice that storage i's payoff $\mathbb{E}[\pi_i] = \sum_{t\in T}\left(\varepsilon^{[t]} + \gamma^{[t]}\right)A^2$ when there is no information available. The additional payoff proportional to $C^2\mathbb{E}[x_i^{[1]}]^2$ corresponds to the economic value of the private forecast:

$$\begin{aligned}\lim_{n\to\infty}\mathbb{E}[\pi_i] &= \lim_{n\to\infty}\sum_{t=1,2}\left(\varepsilon^{[t]} + \gamma^{[t]}\right)\left[\frac{\left(\beta^{[1]} - \beta^{[2]}\right)^2}{(n+1)^2\left(\gamma^{[1]} + \gamma^{[2]}\right)2} + \frac{(1-\delta)^2}{(n-1)^2\left(\gamma^{[1]} + \gamma^{[2]}\right)^2\rho}\right]\\ &\quad \times \lim_{n\to\infty}\sum_{t=1,2}\left(\varepsilon^{[t]} + \gamma^{[t]}\right)\left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}}\right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}}\right)^2\rho^{-1}\right]\cdot n^{-2}.\end{aligned} \tag{20}$$

□

A.4 Proof of Proposition 4

To derive the equilibrium storage quantities, we set $\frac{\partial\mathbb{E}[\pi_i|x_0^{[1]}]}{\partial d_i^{[1]}} = 0$:

$$\left[\begin{array}{c}\beta^{[1]} - \beta^{[2]} - \left(\gamma^{[1]} + \gamma^{[2]}\right)\sum_{j\neq i}\mathbb{E}[d_j^{[1]}|x_0^{[1]}] \\ +\mathbb{E}[\eta^{[1]}|x_0^{[1]}] - \mathbb{E}[\eta^{[2]}|x_0^{[1]}] \\ -2\left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon^{[1]} + \varepsilon^{[2]}\right)\cdot d_i^{[1]}\end{array}\right] = 0. \tag{21}$$

Notice that $\mathbb{E}[d_j^{[1]}|x_0^{[1]}] = A + Bx_0^{[1]}$, since $x_0^{[1]}$ is common knowledge. $\mathbb{E}[\eta^{[1]}|x_0^{[1]}] = \frac{\sigma}{\alpha+\sigma}x_0^{[1]}$, and

$$\mathbb{E}[\eta^{[2]}|x_0^{[1]}] = \mathbb{E}[\delta\eta^{[1]} + \epsilon_1|x_0^{[1]}] = \delta\mathbb{E}[\eta^{[1]}|x_0^{[1]}].$$

By matching the coefficients with respect to $x_i^{[1]}$, we have

$$A = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon^{[1]} + \varepsilon^{[2]}\right) + (n+1)\left(\gamma^{[1]} + \gamma^{[2]}\right)},$$

$$B = \frac{(1-\delta)\sigma/(\alpha+\sigma)}{\left[2\left(\varepsilon^{[1]} + \varepsilon^{[2]} + \gamma^{[1]} + \gamma^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)(n-1)\right]}.$$

The corresponding payoff can be calculated as follows:

$$\mathbb{E}[\pi_i] = \sum_{t=1,2} \left(\varepsilon^{[t]} + \gamma^{[t]} \right) \cdot \left\{ \left[\frac{\beta^{[1]} - \beta^{[2]}}{\sum_{t=1,2} 2\left(\varepsilon^{[t]} + \gamma^{[t]} \right) + (n-1)\left(\gamma^{[1]} + \gamma^{[2]} \right)} \right]^2 + \left[\frac{(1-\delta)}{\sum_{t=1,2} 2\left(\varepsilon^{[t]} + \gamma^{[t]} \right) + \left(\gamma^{[1]} + \gamma^{[2]} \right)(n-1)} \right]^2 \cdot \frac{\sigma}{(\alpha + \sigma)^2} \right\}.$$

$$\lim_{n\to\infty} \mathbb{E}[\pi_i] \to \sum_{t=1,2} \left(\varepsilon^{[t]} + \gamma^{[t]} \right) \left[\left(\frac{\beta^{[1]} - \beta^{[2]}}{\gamma^{[1]} + \gamma^{[2]}} \right)^2 + \left(\frac{1-\delta}{\gamma^{[1]} + \gamma^{[2]}} \right)^2 \cdot \frac{\sigma}{(\alpha + \sigma)^2} \right] \cdot n^{-2}.$$

□

A.5 Proof of Proposition 5

To solve for equilibrium storage quantities, we set $\frac{\partial \mathbb{E}[\pi_i | x_0^{[1]}]}{\partial d_i^{[1]}} = 0$ for $\forall i \in J$ and $\frac{\partial \pi_i}{\partial d_i^{[1]}} = 0$ for $\forall i \in I - J$, separately. For $\forall i \in J$,

$$\beta^{[1]} - \beta^{[2]} - \left(\gamma^{[1]} + \gamma^{[2]} \right) \left[\begin{matrix} (n-m)C+ \\ (m-1)\left(A + Bx_0^{[1]} \right) \end{matrix} \right] = 0,$$
$$+ \frac{(1-\delta)\sigma}{\alpha + \sigma} x_0^{[1]} - 2 \left(\begin{matrix} \gamma^{[1]} + \gamma^{[2]} \\ + \varepsilon^{[1]} + \varepsilon^{[2]} \end{matrix} \right) \cdot \left(A + Bx_0^{[1]} \right) \qquad (22)$$

whereas for $\forall i \in I - J$,

$$\beta^{[1]} - \beta^{[2]} - \left(\gamma^{[1]} + \gamma^{[2]} \right) \left[\begin{matrix} mA+ \\ (n-m-1)C \end{matrix} \right] - 2 \left(\begin{matrix} \gamma^{[1]} + \gamma^{[2]} \\ + \varepsilon^{[1]} + \varepsilon^{[2]} \end{matrix} \right) \cdot C = 0. \qquad (23)$$

Matching coefficients with respect to $x_0^{[1]}$, we can obtain A, B and C following a similar procedure as before. We measure the economic efficiency by aggregate payoff:

$$\sum_{i \in I} \mathbb{E}[\pi_i] = \left(\varepsilon^{[1]} + \varepsilon^{[2]} + \gamma^{[1]} + \gamma^{[2]} \right)$$

$$\cdot \left(nA^2 + \frac{(1-\delta)^2 m}{\left[\begin{matrix} 2\left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon^{[1]} + \varepsilon^{[2]} \right) \\ + (m-1)\left(\gamma^{[1]} + \gamma^{[2]} \right) \end{matrix} \right]^2} \frac{\sigma}{(\alpha + \sigma)^2} \right). \qquad (24)$$

It can be checked that the storages' aggregate payoff $\sum_{i \in I} \mathbb{E}[\pi_i]$ is maximized when

$$m = 1 + \frac{2\left(\varepsilon^{[1]} + \varepsilon^{[2]} \right)}{\gamma^{[1]} + \gamma^{[2]}}. \qquad (25)$$

□

A.6 Proof of Proposition 6

The payoff from storage i under a Lagrangian relaxation can be expressed as

$$L_i \left(d_i^{[t]}, t \in T \right) = \sum_{t \in T} l_i^{[t]} \left(d_i^{[t]} \right)$$
$$= \sum_{t \in T} \mathbb{E} \left[\begin{matrix} P^{[t]}(D^{[t]}) \cdot d_i^{[t]} \\ -\varepsilon^{[t]} \cdot \left(d_i^{[t]} \right)^2 \end{matrix} | X_i^{[t]} \right] - \lambda^{[t]} \mathbb{E} \left[\sum_{t \in T} d_i^{[t]} | X_i^{[t]} \right]$$
$$= \sum_{t \in T} \mathbb{E} \left[\begin{matrix} P^{[t]}(D^{[t]}) \cdot d_i^{[t]} \\ -\varepsilon^{[t]} \cdot \left(d_i^{[t]} \right)^2 - \lambda^{[t]} d_i^{[t]} \end{matrix} | X_i^{[t]} \right],$$

wherein $\lambda^{[t]}$ is a Lagrangian multiplier to relax the constraint that $\mathbb{E}\left[\sum_{t \in T} d_i^{[t]} | X_i^{[t]}\right] = 0$. To solve for equilibrium storage quantities, we set $\frac{\partial l_i^{[t]}\left(d_i^{[t]}\right)}{\partial d_i^{[t]}} = 0$:

$$
\begin{bmatrix}
\beta^{[t]} - \gamma^{[t]} \sum_{j \neq i} \mathbb{E}[d_j^{[t]} | X_i^{[t]}] \\
+ \mathbb{E}[\eta^{[t]} | X_i^{[t]}] - 2\left(\gamma^{[t]} + \varepsilon^{[t]}\right) \cdot d_i^{[1]} - \lambda^{[t]}
\end{bmatrix} = 0. \tag{26}
$$

By $\mathbb{E}\left[\sum_{t \in T}\left(d_i^{[t]}\right)^*\right] = 0$, we use λ as a static approximate solution instead of $\lambda^{[t]}$.

□

A.7 Proof of Proposition 7

Again, the first-order condition for payoff-maximization requires

$$
\begin{bmatrix}
\beta^{[1]} - \beta^{[2]} - \left(\gamma^{[1]} + \gamma^{[2]}\right) \sum_{j \neq i} \mathbb{E}[d_j^{[1]} | x_0^{[1]}, x_i^{[1]}] \\
+ \mathbb{E}[\eta^{[1]} | x_0^{[1]}, x_i^{[1]}] - \mathbb{E}[\eta^{[2]} | x_0^{[1]}, x_i^{[1]}] \\
- 2\left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) \cdot d_i^{[1]}
\end{bmatrix} = 0. \tag{27}
$$

The unknown coefficients in the equilibrium buying or selling quantities are summarized as follows:

$$
A_i = \frac{\beta^{[1]} - \beta^{[2]}}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)} \cdot \left[\sum_{i \in I} \frac{\left(\gamma^{[1]} + \gamma^{[2]}\right)}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)} + 1\right]^{-1}.
$$

$$
C_i = -\frac{\left(1 - \gamma^{[1]} - \gamma^{[2]}\right)\frac{(1-\delta)\rho_i}{\alpha+\sigma+\rho_i}}{\left[2\left(\begin{matrix}\gamma^{[1]} + \gamma^{[2]} \\ +\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\end{matrix}\right) - \left(\gamma^{[1]} + \gamma^{[2]}\right)\frac{\rho_i}{\alpha+\sigma+\rho_i}\right]} \cdot \frac{\sum_{i \in I} \frac{\frac{\rho_i}{\alpha+\sigma+\rho_i}}{\left[2\left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) - \left(\gamma^{[1]} + \gamma^{[2]}\right)\frac{\rho_i}{\alpha+\sigma+\rho_i}\right]}}{1 + \sum_{i \in I} \frac{\left(\gamma^{[1]} + \gamma^{[2]}\right)\frac{\rho_i}{\alpha+\sigma+\rho_i}}{\left[2\left(\gamma^{[1]} + \gamma^{[2]} + \varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) - \left(\gamma^{[1]} + \gamma^{[2]}\right)\frac{\rho_i}{\alpha+\sigma+\rho_i}\right]}}.
$$

$$
B_i = -\frac{\left(\gamma^{[1]} + \gamma^{[2]}\right)\left(\sum_{i \in I} B_i + \frac{\sigma}{\alpha+\sigma+\rho_i}\sum_{j \neq i} C_j\right)}{\left[2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)\right]} + \frac{\frac{(1-\delta)\sigma}{\alpha+\sigma+\rho_i}}{\left[2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)\right]},
$$

wherein

$$
\sum_{i \in I} B_i = -\frac{\sum_{i \in I} \frac{\left(\gamma_i^{[1]} + \gamma_i^{[2]}\right)\frac{\sigma}{\alpha+\sigma+\rho_i}\sum_{j \neq i} C_j}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma_i^{[1]} + \gamma_i^{[2]}\right)}}{\left[1 + \sum_{i \in I} \frac{\left(\gamma_i^{[1]} + \gamma_i^{[2]}\right)}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma_i^{[1]} + \gamma_i^{[2]}\right)}\right]} + \frac{\sum_{i \in I} \frac{\frac{(1-\delta)\sigma}{\alpha+\sigma+\rho_i}}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)}}{\left[1 + \sum_{i \in I} \frac{\left(\gamma^{[1]} + \gamma^{[2]}\right)}{2\left(\varepsilon_i^{[1]} + \varepsilon_i^{[2]}\right) + \left(\gamma^{[1]} + \gamma^{[2]}\right)}\right]}.
$$

□

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