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Competing Under Asymmetric Information: The Case of Dynamic Random Access Memory Manufacturing

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Much like in other semiconductor environments, dynamic random access memory (DRAM) manufacturers face significant demand uncertainty before production and capacity decisions can be implemented. This paper investigates the role of market information in DRAM manufacturing and the consequences of allowing information sharing in the industry. An oligopoly model of competition with correlated private information is developed in which firms make decisions about production and capacity. In this setting, firms consider the information their competitors are likely to hold, conditional on their own. We find that both firms and customers benefit when firms share information with their competitors. In particular, sharing information is profitable because market price decreases slowly with overproduction. When combined with the results from the information sharing literature, this paper highlights the need to assess information sharing policies on a case-by-case basis.

Keywords: marketing; economics; industrial organization; asymmetric information; information sharing; competitive strategy; game theory; market structure
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1. Introduction

Over the last six decades, strategic behavior has remained as one of the centerpieces of economic thought and inquiry. Its prominence is likely to source from its being central to understanding human and institutional behavior, as well as from its intricate features, which naturally attract deliberation.

One of the sources of the intricate features of strategic behavior is that agents may hold different information about the phenomenon at hand. In financial markets, investors can be more or less optimistic about the same asset depending on their private information and the same can be said about economic agents deciding their consumption/savings allocations. In an industrial market, such as the one focused in this paper, companies can be more or less optimistic about future conditions. The reason asymmetric information adds complexity to strategic behavior is that an agent is required to deliberate on the other players' likely actions conditional on the information available privately to her. In market competition situations this assumption is central for decision making whenever agents face significant uncertainty but have some information to spear through it.

This paper focuses on the case of dynamic random access memory (DRAM) manufacturers, the makers of everyday "computer memory" chips, a pervasive component of most electronic products. As with other semiconductor industries, DRAM manufacturers face significant uncertainty about economic outcomes, and market information is vital for their most important decisions, such as production and capacity investments. The analysis investigates how market information shapes this industry at various levels. First, it recovers the fundamental market parameters, including the precision of the information available to the agents. Second, it considers the hypothetical scenario of information sharing across firms, and its impact on firm performance, market volatility, and consumer welfare. Finally, the paper provides an identification argument for a game of asymmetric information and adds to the present knowledge on incentives for information sharing in strategic settings.

Accessing reliable and complete data on public and private information of firms in any market is largely infeasible. Instead, our approach recovers the *unobservable* information that is consistent with *observable* firms' actions by use of a strategic model of competition. The model allows for correlated private information in the sense that, for example, when a firm receives "good news" about future market performance, it is aware that its competitors may be equally optimistic for similar reasons.

The seminal literature on competition and incentives for information sharing (Vives 1984; Gal-Or 1985, 1986) has considered the cases where firms have access to correlated private information about market performance or about their own costs.[1] Gal-Or (1986), who focuses on sharing cost information with competitors, provides the following incisive intuition about the incentives to share information with competitors:

> The pooling of private information about unknown costs has two effects on the firm. On one hand, more accurate information about the rival's cost is available, and the strategies can be more accurately chosen. . . .On the other hand, the pooling of the information reduces the correlation among the decision rules. . . . Reduced correlation has a positive or negative effect dependent upon the slope of the reaction functions of the firms. If they are downwards sloping (Cournot competition) reduced correlation has a positive effect, and if they are upwards sloping (Bertrand competition) reduced correlation has a negative effect. Our main result is consistent with the above discussion. More explicitly, perfect revelation is a dominant strategy at the Cournot equilibria and no revelation is a dominant strategy at the Bertrand equilibria.

By the same reasoning, the dual result holds for the case of sharing information about demand, as shown by Vives (1984): firms benefit from sharing information about demand when their best-response functions are positively sloped (Bertrand competition) but not when their best-response functions are negatively sloped (Cournot competition), because pooling information about the market conditions increases correlation among actions.[2]

This intuition has informed the scarce empirical analyses of competition settings admitting correlated private information. Doyle and Snyder (1999) utilize production plans from the automotive industry in a Cournot setting to identify whether announcements led to competitive reactions. Observing a positive correlation between firm announcements and competitive reactions, they concluded that firms could be using production plans to share information about demand rather than costs. However, their finding is at odds with the predictions of the findings of the theoretical literature described above, under which firms should have no incentive to share demand information in quantity-setting contexts. By considering a more general framework, this paper rationalizes their findings: we recover nonmonotonic best-response functions and find that under these conditions firms do have an incentive to share demand information with their competitors, even when they are quantity setters. However, allowing this flexibility means abandoning algebraic expressions and accepting a significant computational cost as well as a number of numerical approximation methods.

Armantier and Richard (2003) focus on sharing cost information in a duopoly airline setting. Consistent with the predictions of the theoretical literature, they find that airlines deciding how many flights to produce benefit from sharing cost information while they only moderately decrease consumer surplus. However, they do not distinguish between production and capacity decisions by firms (nor do they allow the flexibility discussed above). Instead, they consider each flight as the airline's production decision. By contrast, we explicitly incorporate capacity decisions into our model and show that the quality of information strongly interacts with the capacity available to a firm. For example, a firm with a low capacity level may not be able to take advantage of positive information because its capacity is likely to bind. Given this, information sharing may benefit her competitors but affect her own performance negatively.[3]

Additionally, we find that sharing demand information creates a smoother market (the variance of the firms' payoffs is reduced), and the downstream market also benefits. At the core of our results lies the nonmonotonic nature of the best-response curves that we recover through our empirical application. In this case, theoretical predictions are not available, and assessing the consequences of information sharing becomes mainly an empirical exercise.

Ng and Shum (2007) investigate information and expertise pooling resulting from brokerage service mergers. By comparing earnings forecasts of brokerage firms before and after mergers, the authors find support for occurrence of information pooling. Moreover, at the analyst level, Ng and Shum (2007) propose that postmerger reallocation of analysts to particular stocks is a likely mechanism driving postmerger forecast improvements. Rather than focusing on identifying the benefits of pooling information through mergers and acquisitions, this paper provides the complementary analysis of the incentives of sharing information between a firm and its ongoing competitors.

The next section presents the data sets for the analysis, and §3 outlines the model and the estimation procedure. Section 4 presents the estimation results,

[1] Other seminal contributions include Novshek and Sonnenschein (1982), Clarke (1983), and Shapiro (1986). See also Raith (1996) and Jin (2000) for an integrative analysis. The role of market information in competition has also been analyzed in other contexts. See, for example, Chu (1992), Villas-Boas (1994), and Chen et al. (2001).

[2] Sharing information about market conditions and about costs has a parallel in auction theory, in common value and private value auctions, respectively.

[3] Recent empirical work in auctions has also allowed for the existence of correlated, asymmetric information. For example, Somaini (2015) allows bidders in procurement auctions to hold private cost information, and cost levels are allowed to be correlated across competitors. Somaini finds that this structure helps to explain the lack of a significant relationship between bid aggressiveness and competitors' distance to a project.

and §5 is devoted to the counterfactual analysis. Section 6 provides some concluding remarks.

2. Data

The DRAM market is organized into roughly more than 10 players, many of whom are organized into alliances of firms that effectively share production technologies and coordinate research and development efforts, decide production levels, and allocate available capacity across their members.[4]

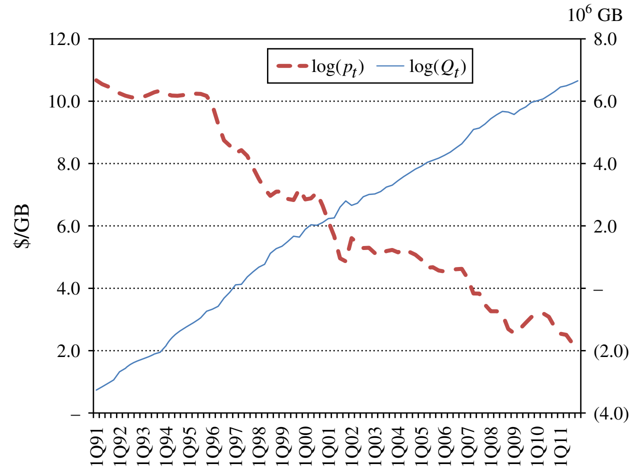
A firm in the DRAM industry provided two proprietary data sets for the model estimation. The first data set is an aggregate series of quarterly price (dollars per gigabyte (GB)) and quantities (10^6 GB) of DRAM from the beginning of 1991 until the end of 2011. This data set is used for estimation of the demand curve. Figure 1 plots the logarithm of quantity and of price over the sample period of 1991–2011.

A second, more detailed data set is used to estimate the supply-side parameters. This data set includes quarterly information from the first quarter of 2005 until the third quarter of 2010 about production, capacity, and cost information of seven firms in the DRAM industry that account for roughly 90% of the market share of the global DRAM market. These firms are organized into four alliances that effectively behave as coordinated organisms and are taken as individual decision-making units in the analysis.[5] Tables 1 and 2 present the descriptive statistics of the data sets.

The memory density indexes (denoted as τ_{it} in the model) were constructed by experts of the data provider and were based on the production technologies each alliance had implemented at each moment in time. Memory density translates directly into production cost. In our case, the indexes measure relative production efficiencies over time and across firms and are normalized such that alliance 1 has an index of 1 at a specific moment in time.

Since 2005 and until the third quarter of 2008, "virtual" capacity usage (not taking outages and maintenance stoppages into account) was at 100% and the DRAM market faced undersupply. The main problem for firms had been to update their production capacity appropriately to be able to sell more units at lower costs. However, from the last quarter of 2008 until late 2009, capacity utilization dropped dramatically. During that period, marginal production costs played an important role in the production levels of firms. At the same time, firms refinanced heavily through their parent companies or through renegotiation with banks to stay in operation.[6] A listing of the firms included in the data as well as of their nationalities and partnerships is provided in Table 3.

Figure 1 (Color online) Logarithms of Market Price and Quantity over Time (1Q1991–4Q2011)



The alliance structure is not always stable. During our sample period, Elpida changed alliances to join ProMOS and Powerchip in 2009. This is incorporated in our analysis by aggregating the cost indexes, production, and capacity levels accordingly.[7]

Producing DRAM implies combining a number of resources. But it is by far the production technology that determines the relevant cost for decision making about output.

South Korean Samsung Electronics is the leader in market share throughout most of the sample period, capturing almost a third of the unit sales in the market. It is followed by Hynix, which achieves more than 20% market share of DRAM unit sales. The remaining chunks of the market are shared among the medium-sized competitors (i.e., Elpida and Micron, with 19% and 13% market shares, respectively) and smaller firms (Powerchip and ProMOS, with less than 6% each).[8]

Whereas production increased for most firms along the sample period (and all firms were producing more in mid-2009 than in the beginning of 2005), capacity usage dropped from full utilization (which occurs until the third quarter of 2008) to roughly 80% until the third quarter of 2009. Finally, market price and production costs follow a downward trend over time,

[4] We outline the main characteristics and history of the DRAM in Web Appendix 1 (available as supplemental material at https://doi.org/10.1287/mnsc.2015.2297).

[5] Conversations with managers suggested that these alliances have power in coordinating research, production, and capacity levels.

[6] The medium-sized player Qimonda (not present in the sample data) was the single casualty after having filed for bankruptcy in the beginning of 2009.

[7] More recently—already outside our sample period, in 2013—Elpida was acquired by Micron. See http://www.micron.com/about/about-the-elpida-acquisition (last accessed January 5, 2016).

[8] See, for example, Howard (2010).

Table 1 Descriptive Statistics of Demand Data Set (1Q1991–4Q2011)

	Min	Max	Mean	Std. dev.
Quarterly industry sales (10^6 GB)	0.04	775.81	103.45	184.31
Market price ($/GB)	8.38	42,926.43	7,794.47	12,396.50

Note. $N = 84$ periods.

Table 2 Descriptive Statistics of Alliance-Level Data Set (1Q2005–3Q2010)

	Min	Max	Mean	Std. dev.
Quarterly industry sales (10^6 GB)	42.16	480.86	201.76	139.43
Market price ($/GB)	12.07	132.36	52.98	39.04
Quarterly industry capacity (10^6 GB)	42.16	480.86	210.99	146.71
Memory density (index)	0.69	2.00	1.28	0.38

Note. $N = 23$ periods $\times$ 4 alliances.

whereas production follows an upward trend over time.

The period covered by the second data set takes place after the complaints by U.S. personal computer makers of collusive behavior by DRAM makers. These claims were proven to be true: they led to heavy penalties to DRAM companies in the years 2003–2005. The executives of some of the most important firms in the industry—Samsung, Hynix, Elpida, and Infineon—pleaded guilty to either keeping artificially high prices through low production levels or obstructing justice in relation to a United States Justice Department's probe on the matter. We assume that by the beginning of 2005 these firms already had incentives to abandon their collusive behavior.

In the next section we present a model in which firms compete "à la Cournot"; i.e., their main strategic variable is production quantity and capacity. We believe this assumption makes sense for a number of reasons. First, the fact that firms kept prices artificially high through low production levels during the 2003–2005 period suggests that production is an important decision variable in the market. Second, the Cournot modeling assumption does not mean that firms are unable to affect other strategic variables such as prices, as illustrated by Kreps and Scheinkman (1983). Finally, the assumption was supported by industry experts of the data provider company.

Because DRAM is often transacted through spot contracts, a Nash bargaining model (Nash 1950) could also appropriately capture the forces in play. However, Nash bargaining does not lend itself naturally to settings of asymmetric information given its axiomatic nature. Another advantage of the Cournot model is its parsimony. For example, the Bertrand–Edgeworth model (see Edgeworth 1925 and Osborne and Pitchik 1986, among other related work) provides another natural modeling alternative because it incorporates capacity levels as well as price setting behavior. However, this model lends itself less

Table 3 DRAM Firms in Sample, Nationalities, and Alliances

Name	Nationality	Alliance identifier
Samsung	South Korea	1
Hynix	South Korea	2
Powerchip	Taiwan	3
ProMOS	Taiwan	3
Elpida	Japan	3, 4
Micron	United States	4

to empirical analysis because of its complexity, often generating multiple and mixed strategy equilibria depending on the particular implementation.[9]

3. The Model

3.1. Preliminaries

This section presents a model of competition where the main decisions of the firms are about setting production and capacity levels. We focus on a repeated two-period model where firms choose capacity levels in the first period and production levels in the second. We discuss the suitability of the modeling assumptions in §3.2.

Consider the problem of the firms in the second period: they decide how much to produce conditional on the installed capacity levels and the available market information. Therefore, in the second period, each firm maximizes its operating profit by solving the problem

$$\pi_i^*(K_i, K_{-i}, \mathcal{I}_2) = \max_{q_i} \; E_\varepsilon[\pi_i(q_i, q_{-i}, \varepsilon) \mid \mathcal{I}_2]$$
$$\text{s.t.} \;\; q_i \le K_i,$$

where q_i is firm i's production level and K_i is its installed capacity level (which was set in the first period). Because firms do not know the market demand shock ε a priori, they condition their expected operating profits on the market information available in the second period, $\mathcal{I}_2$. We assume that this information is public to all firms such that the production game is played under common information. Note that the expected operating profit for firm i, $\pi_i^*(K_i, K_{-i}, \mathcal{I}_2)$, depends on the installed capacity levels for each firm as well as on the available market information. We assume capacities $K_i, i = 1..n$ are observable to all firms during the production stage. In effect, in this industry, firms are aware of others' capacity decisions, and they often publicize their own investments to shareholders.

In period 1, firms decide their capacity levels, which can be used for production in period 2. Hence,

[9] I thank an anonymous referee for pointing out these modeling alternatives. Other forces such as transaction costs also play a role in the industry but are abstracted away in the analysis. Contract-level data would be useful to incorporate such effects.

capacity maintenance generates an option value for production in the second period. We denote the firms' capacity problem in period 1 by

$$\max_{K_i}\{\delta E_{\mathcal{I}_2}[\pi_i^*(K_i, K_{-i}, \mathcal{I}_2)\,|\,\mathcal{I}_{i1}] - \omega_2 K_i^2\}, \qquad (1)$$

where $\mathcal{I}_{i1}$ denotes firm i's information about the market performance available in period 1 and δ is the discount factor. Subscript i in $\mathcal{I}_{i1}$ results from the fact that we allow different firms to have access to different information about the market demand in period 1 while choosing their capacity levels. Hence, in general, firms play a game of correlated information in capacities: firm i invests in maintaining capacity K_i for the next period while incorporating the fact that the actual production constraints of its competitors will depend on their information, which is correlated with its own private information. Solving the capacity game entails finding functions $K_i^*(\mathcal{I}_{i1})\,\forall\, i \in n$ that satisfy the capacity first-order conditions for all possible values of $\mathcal{I}_{i1}$.

We now define $\mathcal{I}_2 \equiv s = \{s_1..s_4\}$ to be a vector of demand signals that is available to all firms in the second period. In period 1 we assume that each firm has access only to its own private information, $\mathcal{I}_{i1} = s_i$. Thus, the information that used to be private to firms in period 1 becomes public in period 2, and as a result, firms play a (correlated) private information game in capacity in period 1 and a common information game in production in period 2. This assumption captures the idea that firms converge on the available information over time, and it is extremely useful to provide tractability to the model. The reason is that it ensures that rivals' capacity investments do not carry informational content to the second period. To see this, consider the case where not all information from period 1 becomes public in period 2. In this case, a firm can use a rival's capacity investment to infer some of the rival's undisclosed private information. However, in this case, strategic firms will take the fact that their capacity investments today can signal their demand information to their competitors in period 2. This strategic behavior adds an undesirable degree of complexity to the model and, moreover, found little support in conversations with industry experts.

Given the assumed information structure and introducing the time subscript, the capacity game becomes

$$\max_{K_{it}}\{\delta E_{s_{-it}}[\pi_{it}^*(K_{it}, K_{-it}, s_t)\,|\,s_{it}] - \omega_2 K_{it}^2\}. \qquad (2)$$

3.2. Discussion of Main Modeling Assumptions

Although analytical models are always stylized representations of reality, it is worth considering how the assumptions of the model above capture the essential factors of the DRAM industry.

Consider first the repeated-game assumption that implies that investments in capacity today carry no dynamic effects to subsequent capacity investments. This assumption is natural in the DRAM industry once the capacity cost $\omega_2 K_{it}^2$ is considered as the cost of maintaining an active capacity level K_{it} rather than capturing the total investment in capacity by firm i at time t. The reason is that the rate of increase of the total theoretical capacity is coordinated through Moore's law: firms invest in production technologies that translate into higher memory densities and, as a result, into higher capacity levels (and lower production costs) over time. Moreover, they also build new facilities to implement these new technologies in novel production lines. This behavior is fixed such that it is well known in the industry that a firm unable to accompany Moore's law is doomed to either exit or to an acquisition by its rivals in the near future. In sum, the capacity investment in the model can be thought of as "variable" capacity cost of maintaining a certain amount of capacity active for production, whereas total investments in capacity are coordinated across firms to accompany Moore's law. As a result, this coordination yields small changes of capacity levels over time, in contrast with some other industries where capacity follows large discrete jumps (see Ryan 2012 for an example of the cement industry).

Although the repeated-game assumption somewhat restricts the use of the model to other settings, it is equivalent to an infinite time-horizon model where firms face additively separable investment costs such that capacity yields a scrap value after it is used or, alternatively, where firms face a "lease" market for capacity such that they can outsource capacity on a variable basis. A proof is presented in Appendix A. The equivalence relies on our focus on Markov perfect equilibria (MPE) as well as on an additive-symmetric separability assumption. The MPE assumption ensures that firms take the same information in both versions of the game (repeated two period and infinite horizon) into account. We also require demand signals to be additively separable over time (be independent over time or follow an autoregressive process of order 1, for example) and that capacity adjustment costs be similarly additively (and symmetrically) separable. The separability assumption ensures that we can move payoffs in time by applying the appropriate discounting while keeping the equilibria strategies of the firms constant. The equivalence assigns a particular meaning to parameter ω_2 in the infinite-horizon version of the game: it captures the net cost of investing in capacity today and receiving a residual payoff for that capacity after it is used (because of utilization and depreciation, etc.).[10].

[10] Although there exist many examples of empirical work on dynamic market competition settings that include private information (e.g., Pesendorfer and Schmidt-Dengler 2003, Bajari et al. 2007, Aguirregabiria and Mira 2007, Ryan 2012, Fershtman and Pakes 2012,

The timing of the investments in production and capacity levels in the model also approximates the reality of the DRAM industry: production decisions take about one quarter (one period) to be implemented and brought to the market. This justifies the assumption that not all information is revealed to firms before making their production decisions. Capacity decisions are also adjustable in the short run: for example, during the financial crisis of late 2008, some firms in the DRAM industry were able to react relatively quickly by divesting in capacity. However, the lag of capacities is longer than that of production, and so we keep the decision sequence of the game presented above during the analysis. Note that the important feature of the timing of the model is that at the time of production, firms still face market uncertainty, which we estimate. We assume that the market clears and that each firm keeps only insignificant levels of inventory. Finally, this assumption relates to the fact that interface and packaging specifications of DRAM chips change fast, which makes the value of unsold production low and a second-order concern for our purposes.

Whereas the information structure benefits the model tractability, it has parallels with the real world. The idea that information becomes better and more similar across firms as time elapses finds backing in at least two ways in this industry. First, DRAM manufacturers publish quarterly results, which often have relevant financial information and forecasts for their shareholders but also for their competitors. Second, a significant amount of customer orders have already been received one quarter before final sales occur. These orders give firms a good idea of how the market will perform until the end of the quarter. That exclusive relations are not pervasive in this market means that DRAM manufacturers deal with similar customer pools. This causes customer orders—and as a result, short-run demand information—- to be correlated. Other sources such as reports from market research companies and the disclosure of economic indicators further make the available information to DRAM manufacturers become better and more similar over time. Finally, it is unlikely that there exist significant informational advantages in this market because of the relatively low costs of gathering information when compared with those of production, capacity investments, and personnel. This hypothesis could be tested if more data were available to identify the full covariance matrix of the information signals. This could matter for the analysis: if demand signals were found to be further correlated across firms, keeping all else constant, it is likely that the magnitude of the incentives for information sharing would be affected.

3.3. Implementation and Estimation

This section outlines an empirical strategy that is easily adaptable to a variety of competition games with private correlated information, under parametric assumptions. First, the demand parameters are estimated and the demand shocks are recovered. Second, the quantity and capacity first-order conditions are used to estimate the parameters associated with the cost of adding quantity and capacity, as well as the noise of the demand signals, σ_η^2. The second step incorporates the recovered demand shocks from the first stage in order to increase efficiency. The estimation searches for the parameters that match the moments of the data with the moments predicted by the model best. A step-by-step description of the methodology is provided in Appendix B.

3.3.1. Demand and Information Structure. DRAM is a significantly commoditized product and is sought primarily by electronic product manufacturers. Spot contracts are the norm and long-term contracts seldom take place. Firms are assumed to face a flexible inverse demand curve for a homogeneous good:

$$P_t = P(\theta, Q_t, \varepsilon_t), \quad \varepsilon_t \sim F_\varepsilon(\cdot), \tag{3}$$

where P_t is the market price, Q_t is the aggregate production, θ is a set of demand parameters, and ε_t is an a priori unknown demand shock that influences the market willingness to pay for each unit of the good. The demand shock ε_t reflects the total market uncertainty under absence of additional information by firms. Although they do not observe the shock directly, firms hold noisy information about the demand shock in the form of a signal $s_{it} = h(\varepsilon_t, \eta_i)$, $\eta_i \sim F_\eta(\sigma_\eta)$, where σ_η^2 captures the noise associated with the demand signals available to the firms. For example, holding all else constant, a lower σ_η^2 signifies that firms have more precise information about the market. We assume the following flexible inverse demand curve specification:

$$P_t = (1+\mu\lambda+\beta(Q_t^\lambda-1))^{1/\lambda}\varepsilon_t,\ \varepsilon_t \sim \mathrm{LogN}(0, \sigma_\varepsilon), \tag{4}$$

where P_t is the market price in period t given parameters μ, β, and λ, as well as the total output Q_t and the market demand shock ε_t. This specification is flexible as it converges to the linear case as λ approaches 1 and to the constant-elastic demand

Bajari et al. 2015), they do not allow for counterfactual analysis with correlated private information. The resources dedicated to the estimation of this model (24 modern computers, each parallelized across eight cores) illustrate the additional obstacles involved in incorporating state dependence in capacity investments with private correlated information curve as λ approaches 0. In between these cases, the parameter λ affects the curvature as well as the level of the demand curve. The multiplicative error specification ensures that the market price has positive support. Moreover, this specification also ensures that the deterministic component of demand does not dominate the stochastic component over time, and vice versa.

Economic activity variables such as North American and world gross domestic product did not attain statistical significance. Thus, they were not incorporated in the final demand specification.[11]

In many empirical applications, demand shocks are assumed to be observable to the firms but not to the researcher. We relax this assumption by allowing firms not to observe the demand shocks with perfect foresight either. Instead, they receive informative demand signals according to

$$s_{it} = \varepsilon_t.\eta_{it}, \ \eta_{it} \sim \mathrm{LogN}(0, \sigma_\eta), \tag{5}$$

such that the signal of each firm is "centered" at the true demand shock but is affected by a noisy component η_{it}. We assume that the demand shocks are independently distributed over time, but it is possible to fit a stochastic process to model their transitions.[12] This assumption deserves a brief discussion. In an ideal setting, one would use the underlying firms' beliefs to impose further structure on the intertemporal distributions. However, this alternative is not feasible because it implies identifying the process that managers believe are responsible for the evolution of the demand shocks and, consequently, of the demand signals. Although we have no reason to believe that the demand-side parameter estimates will be affected by assuming that the demand shocks are independent and identically distributed, the assumption may introduce attenuation bias to the estimate of parameter σ_η^2. The reason is that the model will attribute the firms' decisions to their present information, disregarding the possibility that their actions were also based on additional past information. Because of this, we perform all postestimation analyses at different levels of σ_η^2 to evaluate the counterfactual scenarios at several levels of signal-to-noise ratios. Given the nonlinearity of the model, it is impossible to predict or rule out the resulting biases on the remaining supply-side parameters. This identification limitation is common and has yet to be successfully addressed by the empirical literature of games with correlated private information.

Although input prices are a popular choice for demand instruments, they are mostly irrelevant in the DRAM industry.[13] The main production factor is the density technology in place, which drives managers' decisions on production and capacity. Hence, we use Moore's law (as well as its second and third powers) as an instrument for the production level.[14] The two-step generalized method of moments was used for estimation, based on the consistency properties of methods of moments. The covariance matrix is estimated through the vector autoregressive heteroskedasticity autocorrelation consistent (VARHAC) procedure (see den Haan and Levin 1994, 1997), which accounts for arbitrary correlation patterns in the demand shocks.

3.3.2. Production Decisions. Firms decide how much to produce one period ahead of taking units to the market. Production decisions are constrained by capacity levels and are affected by the demand information and cost structure. Let $\bar{P}_t(\theta, Q_t)$ denote the deterministic part of the inverse demand function. Firms are assumed to face constant marginal production costs c_{it}, which are decomposed as

$$c_{it} = \omega_0 \tau_{it} e^{\omega_1 t}. \tag{6}$$

The parameter ω_0 provides a baseline level for the marginal cost, and parameter ω_1 captures changes in costs over time. Parameter ω_1 captures additional time-varying cost factors unrelated to the technological process, such as personnel costs. The scalar τ_{it} is a relative measure of cost (an index of each firm's memory density in each period) available from the data provider.

Given the demand and information structures above, in each period the production problem of firm i can be written as

$$\begin{aligned} \max_{q_{it}} \ & E_{\varepsilon_t}[\bar{P}_t(\theta, Q_t)\varepsilon_t - c_{it} \mid s_t] q_{it} \\ \text{s.t.} \ & q_{it} \le K_{it}, \end{aligned} \tag{7}$$

which yields the set of Kuhn–Tucker conditions

$$\left(\bar{P}_t + \frac{\partial \bar{P}_t}{\partial q_{it}} q_{it}\right) E_{\varepsilon_t}[\varepsilon_t \mid s_t] - c_{it} - \lambda_{it} + \lambda'_{it} = 0,$$
$$\lambda_{it}(K_{it} - q_{it}) = 0,$$
$$\lambda'_{it}.q_{it} = 0,$$
$$\lambda_{it}, \lambda'_{it}, q_{it} \ge 0,$$
$$q_{it} \le K_{it}.$$

[11] We further comment on the static demand assumption in §4.1.

[12] An example of embedding serial correlation to the full model specification is available upon request. The supply-side model becomes more complex but remains well specified.

[13] For example, no significant relation was found between DRAM production and prices of silicon.

[14] This series is started at a constant value and is discounted in each quarter such that it halves every two years. The efficiency indexes were also used as alternative instruments, and the resulting estimates were very similar.

When considering production decisions, firms take the vector of signals s_t into account. Given the assumptions on the information structure, it follows that

$$\varepsilon_t \mid s_t \sim \mathrm{LogN}\left(\frac{\sigma_\varepsilon^2}{n\sigma_\varepsilon^2+\sigma_\eta^2}\sum_{i\in n}\log(s_{it}),\, \frac{\sigma_\varepsilon^2\sigma_\eta^2}{n\sigma_\varepsilon^2+\sigma_\eta^2}\right), \quad (8)$$

such that the conditional expectation of the demand shock given the available demand signals assumes the "closed-form" expression

$$E[\varepsilon_t \mid s_t] = \exp\left\{\frac{\sigma_\varepsilon^2}{n\sigma_\varepsilon^2+\sigma_\eta^2}\sum_{i\in n}\log(s_{it}) + \frac{1}{2}\frac{\sigma_\varepsilon^2\sigma_\eta^2}{n\sigma_\varepsilon^2+\sigma_\eta^2}\right\}. \quad (9)$$

We now describe the construction of the quantity-related moments for the estimation. These moments are constructed through generating demand signals centered at the recovered demand shocks. Given a guess of the parameters, realizations of η_{it} are simulated and are multiplied by $\hat{\varepsilon}_t$, according to expression (5). This method incorporates the error terms recovered from the first stage of the estimation, which are a function of the estimated demand parameters, and greatly increases the efficiency of the estimation procedure. Note that one only needs to simulate the sum of the logarithms of the demand signals, $\sum_{i\in n}\log(s_{it})$, rather than each of the vector's components, according to the expression of $E[\varepsilon_t \mid s_t]$.[15] The Kuhn–Tucker conditions are then solved for each draw of this statistic, and the average equilibrium quantities for each time period are computed.[16] Rather than simulation, the implementation of a one-dimensional Gauss–Hermite quadrature was extremely beneficial since it required solving for the equilibrium a smaller number of times.

The estimation procedure looks for parameters that match the moments of predicted quantity by the model with those of the data. Let the predicted production by the model be given as $\hat{Q}_t \equiv E_{s_{it}\mid\hat{\varepsilon}_t}(\sum_{i\in n} q_{it}^*(s_{it}))$, i.e., the sum of the equilibrium quantities at the parameter guesses, where quantities are averaged across the simulated demand signals for each period. The first two moments of the quantity distributions from the data and from the model are matched: $E_t[Q_t^l - \hat{Q}_t^l]$, $l = 1..2$.

[15] This method is only applicable to the quantity moments because at that stage information is common knowledge.

[16] There exist $3^4 = 81$ possible configurations for the equilibrium outcome. An exhaustive search was unable to find even a single occurrence of multiple equilibria arising in the quantity stage. The assumption of single equilibrium existence is used to speed up estimation (this assumption allows the algorithm to stop trying different corner configurations once one is found to satisfy all Kuhn–Tucker conditions). In addition, a frequency matrix was used to keep track of the most popular solutions at different values of the simulated signals and costs in order to increase the estimation speed by inspecting likely outcomes first.

These moments identify the cost parameter ω_0 as well as the variance of the demand signals σ_η^2, because production cost affects mainly the mean level of production, and the noise in the demand information (σ_η^2) affects mainly the variance of production. The latter identification argument is further explained in §3.3.4. Because the demand signals also influence the capacity decisions, additional moments are used to infer σ_η^2, as we describe in the next section.

3.3.3. Capacity Decisions. Firms choose capacity investments to maximize expected profits. Let $\delta\pi_{it}^*(K_{it}, K_{-it}, s_i) - \omega_2 K_{it}^2$ be the discounted equilibrium profit of firm i at time t of choosing capacity level K_{it}. The payoffs associated with increasing K_{it} marginally are given by the left-hand side of the first-order condition:

$$\frac{\partial}{\partial K_{it}}\left\{E_{s_{-it}}[\delta\pi_{it}^*(K_{it}, K_{-it}, s_i) - \omega_2 K_{it}^2 \mid s_{it}]\right\} = 0,$$
$$i = 1..n,\ \forall s_{it} \geq 0, \quad (10)$$

The structure of the problem reveals that when choosing its capacity, firm i not only uses its own private information to consider the market conditions but also needs to consider the signals about demand her rivals are likely to hold. The solution satisfies a perfect Bayesian equilibrium in which each firm holds beliefs about the likely types of the other firms, given its own. In the current setting, a firm type is determined by its own private demand signal in each period as well as its cost (which is common knowledge). Given this information, the firm updates the probabilities over the types of the remaining firms according to the probability density function $f_{s_{-it}\mid s_{it}}$, which is presented in Web Appendix 2. There is no need to assign off-equilibrium path beliefs: the event of a firm investing an unexpected amount in capacity is inconsequential because the firm's demand signal becomes public to all firms in the next period.

By solving the first-order conditions associated with the marginal effect depicted in Equation (10), one can recover the optimal capacity policies $K_{it}^*(s_{it})$. However, this problem is not trivial because the firm's profits are a function of its rival's *optimal* policies $K_{jt}^*(s_{jt})$, $j \neq i$, over which the firm is required to take expectations. Moreover, the firm's first-order condition is a function of the demand signal s_{it}, and each level of the signal affects the expectation term $E_{s_{-it}}(\cdot \mid s_{it})$. Technically, this problem is analogous to that of an auction with correlated valuations with rather complex payoff functions because it nests a production game, and it is essentially characterized by a continuum system of equations. We describe the solution strategy in more detail in Appendix B as well as in Web Appendix 2.

Once the system of capacity first-order conditions is solved for each time period in the data, the capacity policy functions $K^*_{it}(s_{it})$, $i = 1..n$ are used to calculate the predicted expected capacity by using single-dimensional quadratures of $s_{it} \mid \hat{\varepsilon}_t$. This provides a numerical approximation of the predicted expected capacity level, $\hat{K}_{it} = E_{s_{it} \mid \hat{\varepsilon}_t}(K^*_{it}(s_{it}))$, centered at the recovered demand shocks from the first-stage estimation, to increase efficiency. As before, the first and the second moments of capacity levels are used. In addition, the moments $E_{i,t}[K_{it}K_{jt} - \hat{K}_{it}\hat{K}_{jt}]$ and $E_{i,t}[(K_{it} - K_{it-1}) - (\hat{K}_{it} - \hat{K}_{it-1})]$ are introduced to capture the average capacity covariance across firms and capacity growth, respectively. These help identify parameters σ^2_η and ω_2, as we describe in the next section.

3.3.4. Identification. The demand function parameters are identified through the conditional independence of the errors with the instruments and with the assumption that the logarithm of the error has mean of zero. Moore's law is used to instrument production quantity, because it relates to investments in cost reductions but is independent of demand shocks. Given that Moore's law provides time-series variation, the exclusion restriction is satisfied by the assumption that demand is stable over time once production is included. Using the memory densities (cost shifters) rather than Moore's law produced very similar results. Memory densities were not kept in the estimation, however, because they could eventually depend on the cost-cutting efforts by firms, which could in turn be correlated with demand shocks.

The cost parameters ω_0 and ω_1 are identified by matching the moments $E_t[Q_t]$ and $E_{i,t}[K_{it} - K_{it-1}]$. In particular, the first moment matches the data's mean production with the one predicted by the model, identifying parameter ω_0. The second moment matches the change in capacity levels with those predicted by the model, over time. This moment helps explain trends in capacities over and above the trends implied by the memory densities τ_{it}, and it identifies parameter ω_1. The capacity cost parameter ω_2 is primarily identified by the moment $E_{i,t}[K_{it}]$, which matches the average industry capacity with the model prediction. Finally, the information parameter σ^2_η is identified by matching the data moments $E_t[Q^2_t]$, $E_{i,t}[K^2_{it}]$, and $E_{i,t}[K_{it}K_{jt}]$, since this parameter affects the variance and covariance of production and capacities. The first two moments inform parameter σ^2_η: as this parameter increases, firms become less sensitive to the available information and their actions become less correlated with the demand shocks. Because of this, the variances of production and capacity levels, holding everything else fixed, decrease as σ^2_η increases. Finally, the information parameter also influences the covariance of capacities because as σ^2_η increases, firms' demand information becomes less similar, leading the covariance in capacities to decrease.

Table 4 **DRAM Demand Parameter Estimates**

Parameter	Coefficient	Std. error
μ	8.624	0.006
β	−0.938	0.445
λ	0.007	0.179
σ^2_ε	0.180	0.028
Observations	84	
R^2	0.968	

4. Results

4.1. Demand-Side Results

Table 4 presents the demand curve parameter estimates.

The most relevant result from the demand estimation is that the curvature parameter λ is not significant, which means that the demand curve is indistinguishable from a constant-elastic demand specification. The inverse of parameter β provides an estimate of the price elasticity, which is approximately equal to −1.07.[17]

The standard error of $\hat{\sigma}^2_\varepsilon$ is calculated using the maximum-likelihood estimator for the constant-demand elasticity demand specification. The estimates of the demand parameters are introduced into the second stage of the estimation. Moreover, the estimates of the demand shocks $\hat{\varepsilon}_t$, which are a function of the parameter estimates, are also included to improve estimation efficiency.

A common question in the industry is whether it is the lower production costs or the market expansion that explain the output increase over time. In Web Appendix 3 we show that under a common information assumption Moore's law suffices to explain the output growth; i.e., no market expansion is required.

4.2. Supply-Side Results

The supply-side parameters were recovered through an efficient two-step simulated method of moments. The parameters are presented in Table 5.

The cost parameters ω_0, ω_1 recover the variable costs per gigabyte of DRAM produced. Figure 2 displays the implied average profit margin for the industry. In line with managerial accounts, the model states that production was sold below cost near the 2008 financial crisis period. In contrast to competition models of perfect information, our model can rationalize this scenario because it allows firms not to have perfect foresight over future demand while making their production decisions. Parameter ω_2 captures the idea that the net cost of capacity is positive.

Parameter σ^2_η captures the noise of the logarithm of the demand signals, and it consequently affects

[17] In Web Appendix 2 we show how we take advantage of the constant elastic result to make the second stage of the estimation faster.

Table 5 Dynamic Parameter Estimates

Parameter	Coefficient	Std. error
ω_0'	0.268	0.028
ω_1	−0.060	0.010
ω_2	0.864	0.104
σ_η^2	0.132	0.052

Note. Above, $\omega_0' \equiv 10{,}000.\omega_0$ so as to standardize the magnitude of the parameters during estimation.

the posterior variance of the demand shocks.[18] When demand signals are not available to firms, the variance of the demand shocks implied by the estimates is of 23.6%. This figure reduces to 9.1% when the firm has access to its own private demand signal (which informs capacity decisions) and reduces further to 2.9% when all demand signals are revealed (these inform the quantity decisions). In line with this result, the correlations between the recovered market demand shocks and the capacity and the production levels are 0.28 and 0.37, respectively.

An example of the recovered capacity policy functions is provided in Figure 3. These policies increase in the demand signals and differ across firms because of differences in cost levels. The model seems flexible enough to adapt to the moments of the data.[19] Figure 4 plots the predicted and actual aggregate quantities and capacities. Visual inspection suggests that the model predictions seem to fluctuate more than their data counterparts (although their variances are smaller, according to Table 1 in Web Appendix 4). One possibility to solve this apparent misfit would be to add more degrees of freedom to the information structure in order to match the moments in the model with those in the data better.

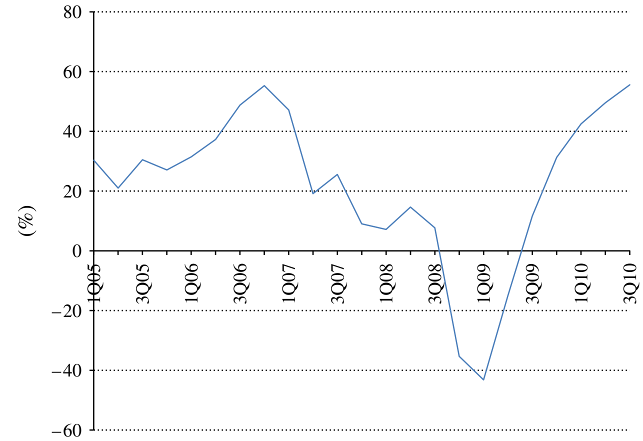
The differences between the lines have a precise structural interpretation. When the model overpredicts production or capacity levels it means that the firms received pessimistic demand signal realizations, although on average they would be expected to receive higher demand signals. An interesting example is provided by the period near the 2008 financial crisis, where the model underpredicts both production and capacity levels. The underlying interpretation is that in this period, firms received overly optimistic demand signal realizations, which led them to overproduce and overinvest in capacity in a time of (ex post) low demand shocks. This is a common opinion of managers in the industry.

As explained in the introduction, the best-response curves of the perfect information game may inform

[18] The analytical expressions for the relevant variances follow from the log-normal distributional assumptions. Their derivation is available upon request.

[19] Measures of fit are presented in Web Appendix 4.

Figure 2 (Color online) Average Estimated Industry Profit Margins (1Q2005–3Q2010)



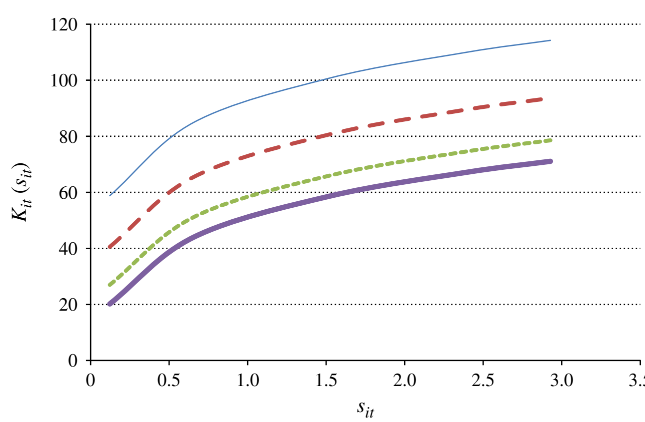
Notes. The estimated industry profit margins, given by $(p_t - \hat{c}_t)/p_t$, do not display trends. This is because both price and costs decrease over time. According to interviews to managers, production took place below cost in the period following mid-2008. This is rationalized by the fact that firms face demand uncertainty before making quantity decisions.

the incentives for sharing information in the private information game. Consider the demand function in the present model:

$$P_t = (1 + \mu\lambda + \beta(Q_t^\lambda - 1))^{1/\lambda}\varepsilon_t. \tag{11}$$

We inspect the capacity best-response curves at the recovered parameters and contrast them to the linear case. In particular, we solve the game for alliance 1 and calculate $E_{s_1}[K_1^*(s_1)]$ while fixing K_{-1} for the other firms at different levels. Figure 5 plots the best-response curves of capacity for the linear case and for the demand function implied by the parameter estimates. When demand is linear, the capacity levels are strategic substitutes; i.e., the best response to

Figure 3 (Color online) Equilibrium Capacity Policies as a Function of the Private Demand Signal



Notes. The equilibrium capacity policies, approximated by cubic splines, increase with the private demand signals. The graph above uses the demand- and supply-side parameter estimates as well as the costs of the last observation in the data set.

Figure 4 (Color online) Actual and Predicted Capacities and Quantities (1Q2005–3Q2010)

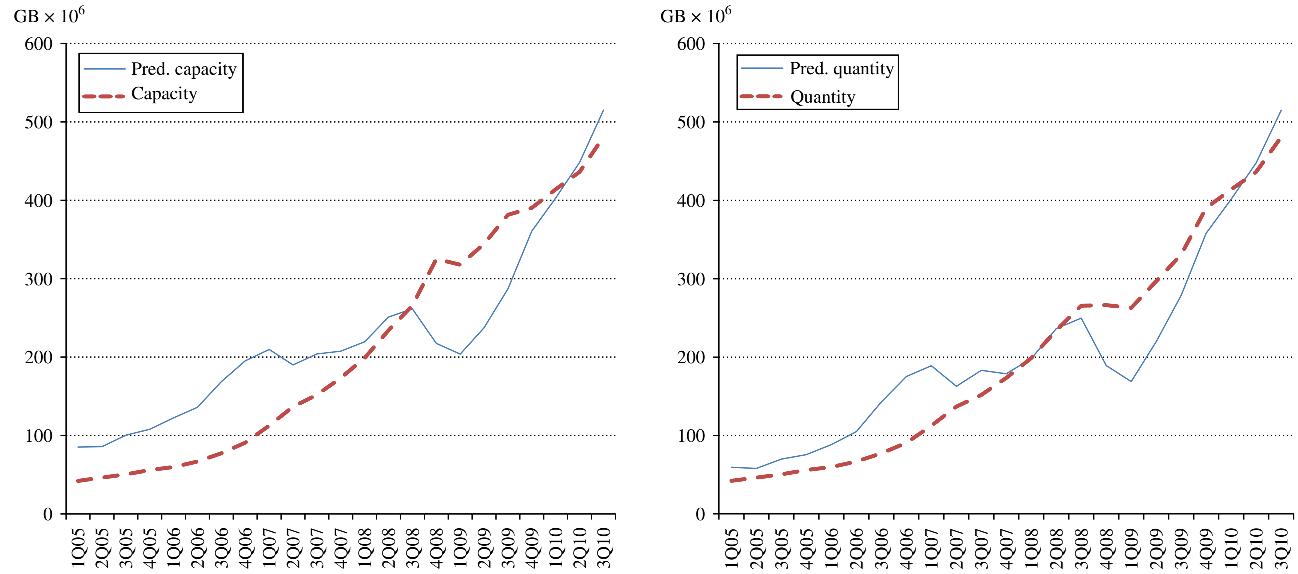
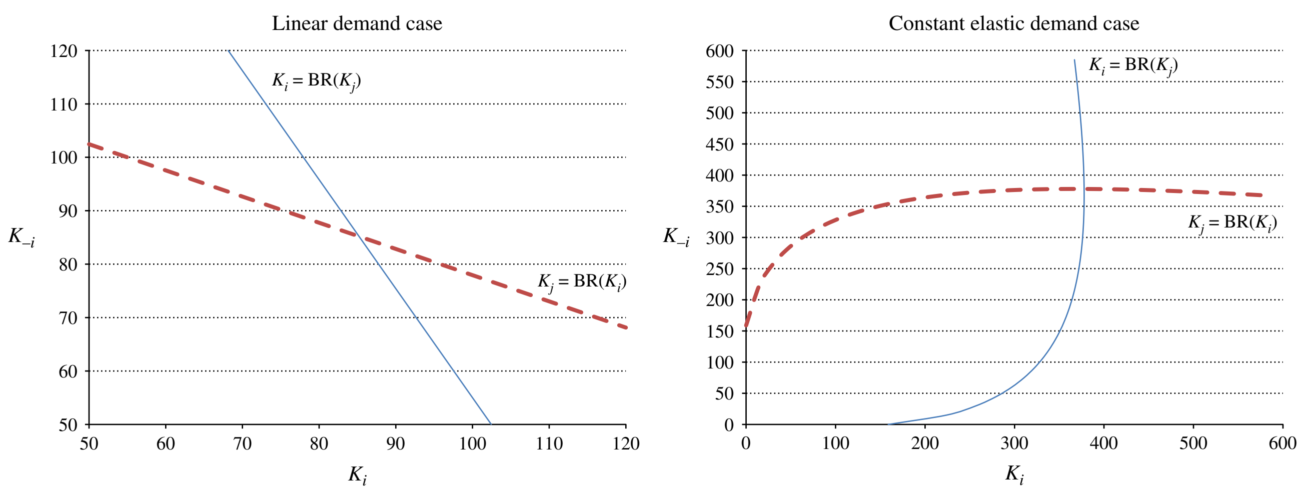


Figure 5 (Color online) Best-Response Curves of Capacity in a Duopoly Under Common Information



rivals' increases in capacity is to always lower one's own capacity level. This does not hold, however, in the case of constant elastic demand. In this case, the firm's optimal policy is to increase its capacity when the rivals increase their capacities from low levels but to reduce it when the rivals' capacities increase from high levels. In fact, although we do not show them here, these best responses are quite similar to the underlying production best responses of the production game.[20]

In light of the previous discussion on the incentives for information sharing, predicting the effect of information quality and sharing on the market is not trivial since the firms' best-response curves are nonmonotonic. Hence, the empirical analysis is especially suited to analyze these questions further.

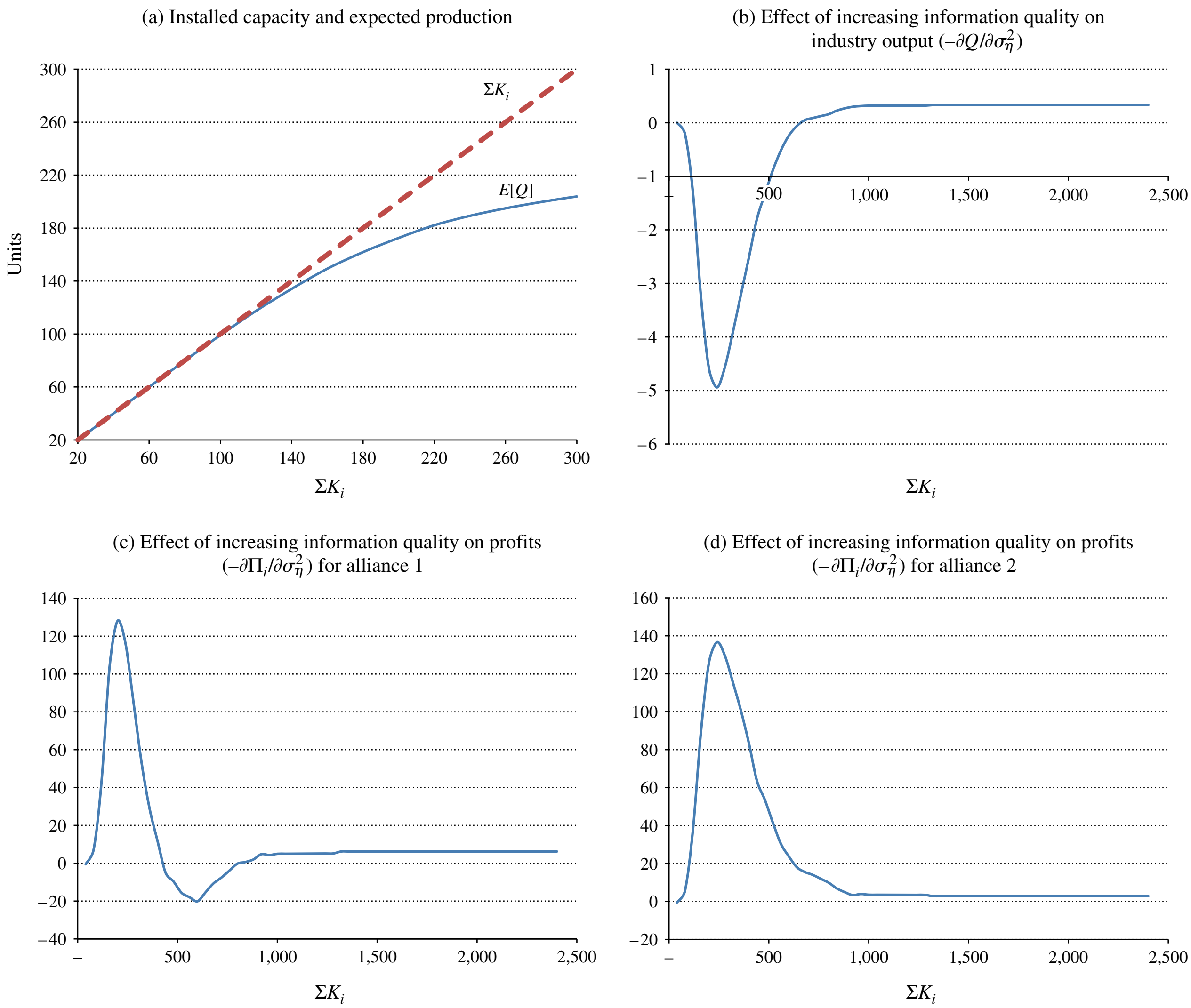
5. Counterfactual Analysis

5.1. Information Quality, Capacity Constraints, and Industry Performance

In this section, we assess how the quality of the information available to firms affects the competition in the second stage. The quality of the information available to firms may change because of several reasons, such as the introduction of a new technology or the entrance of a new information gatherer agency. Here, we investigate how these shocks affect the quantity competition stage and industry operating profits.

[20] Firms' best responses are nonmonotonic when they face a constant elastic demand function in Cournot. See Martin (2002) for a discussion. Moreover, the production problem yields an algebraic solution, as shown in Appendix B.

Figure 6 (Color online) Operating Profits, Capacities, and Information Precision



Parameter σ_η^2 captures the informativeness of the demand signals to the firms. As σ_η^2 approaches zero from above, the demand signals become better predictors of the true demand shocks.[21] Moreover, we also investigate how the presence of (exogenous) capacity constraints affects the quantity game.[22] In particular, we inspect the *expected* operational profit

$$\pi^*_{it,\,\sigma_\eta^2}(K_{it}, K_{-it}, s_{it}). \tag{12}$$

In this analysis, we constrain the individual capacities in vector K_t to be equal, for simplicity. Figure 6 depicts the role of capacities on production decisions and industry profits. Panel (a) shows that the average production is always below the available capacity and that it also increases slower. The reason for the latter phenomenon is that when capacity is low, it is very likely to bind, and so production and capacity increase hand in hand. However, when capacity is high, it is not always profitable for firms to exhaust it.

Panel (b) depicts the marginal effect of improving the quality of the demand shocks (i.e., lowering σ_η^2) on industry production at different levels of installed capacity. To understand these patterns, one needs to consider the behavior of firms when facing different demand signals. First, the higher the quality of a demand signal, the more a firm will trust it. Hence, a firm is willing to increase its production more when it receives a positive signal that is of higher quality. Conversely, if a firm receives a low demand signal, it will decrease its production to the extent it believes

[21] Whereas the use of the log-normal information structure means that varying σ_η also affects the conditional mean of the demand signals, the posterior mean of $\varepsilon\,|\,s$ remains constant. This means that changes to the parameter σ_η affect profits through noise and not through changes in levels.

[22] The interaction between endogenous capacity constraints and signal informativeness is discussed in the next section.

it to be a good indicator of the true demand shock. Because positive demand signals increase production and negative demand signals reduce it, the average outcome is ambiguous. However, in Cournot settings, firms fear overproduction on average: if all firms receive positive demand signals when demand was actually low, the market price suffers and each firm loses. As the quality of the demand signal increases, this fear is reduced and firms are willing to produce more. This is consistent with panel (b) at high levels of capacity (when capacity is unlikely to bind).[23] Consider now the intermediate area: in this region, capacity is relatively likely to bind. As the information quality increases, firms react more to the same demand signals by increasing and reducing demand appropriately. However, because they cannot produce more than the installed capacity when they receive positive signals, the average effect of the positive and negative demand signals becomes negative. In this case, firms would prefer to increase production more when they receive positive signals; however, they cannot because they face a production constraint. Finally, when capacity tends to zero, changes in σ_η^2 have a negligible effect on production.

How do capacity constraints affect the relationship between the quality of the information and profits? Panels (c) and (d) depict the marginal effect of improving demand information (decreasing σ_η^2) on the operational profits of alliances 1 and 2. Recall that alliance 1 (Samsung) is an industry leader with lower production costs than the remaining alliances. When capacity is very high, better information improves firms' profits. The reason is that under constant-elastic demand, the direct effect dominates the competition effect, and firms benefit when the industry has access to better information. This is related to the nonmonotonicity of the best-response curves, which makes this result not predictable a priori. Moreover, the result can be reversed when capacity is likely to bind. In particular, note that alliance 1 can become worse off in an intermediate region if all firms have access to better information. In this region, alliance 1's capacity is more likely to bind than the others because of its low production cost. When firms receive the same positive signal with lower variance, they react more to it by producing more. However, alliance 1 is unable to produce more because of its capacity constraint, and so its profits decrease because of the resulting lower market price. Alliance 2, panel (d) provides the representative case for the remaining firms, for which better information always results in higher profits.

These results have a short-term nature because of the exogenous levels of installed capacity. However, given its lower production cost, alliance 1 is likely to have higher incentives to invest in capacity to start with, and these effects may not hold in the equilibrium of the full game. Hence, the next section considers the incentive to share information when capacities are decided endogenously.

5.2. Information Sharing and Firm Profits

Do firms benefit from sharing information? An example of such a policy would be the case in which firms shared their demand information directly or through a third party, which would then distribute it to the industry. Here, we assume it is possible to share at least some information with competitors in a credible fashion, à la Vives (1984) and Gal-Or (1985, 1986).[24] Under the shared information structure, firms solve the problem

$$\max_{K_{it}}\left\{\delta\pi_{it}^*(K_{it}, K_{-it}, s_t) - \omega_2 K_{it}^2\right\} \tag{13}$$

in which they all have access to the same vector of demand signals, s_t. The solution of this problem can be achieved in a similar way to the one used to solve the problem with private information. The interpolation method described before is used to solve problem (13) where firms have access to a full vector of information signals s_t rather than just their private information signal s_{it}.[25] Figure 7 depicts the benefits of sharing demand information for each firm along different values of information precision. Values to the right—high σ_η^2—describe scenarios where the available information is of low quality, whereas values to the left—low σ_η^2—depict cases in which the quality of the information available to firms is high.

It is clear that sharing information is beneficial for all firms. This is enabled by the slope of the capacity best-response curves being positive for a relevant portion of the capacity domains. The profits in both scenarios are most similar when information is perfect ($\sigma_\eta^2 \to 0$) and when information is very noisy ($\sigma_\eta^2 \to \infty$). As expected, in these cases there is no benefit to share information with competitors. This result is novel in a quantity-setting context, and moreover, it rationalizes the findings of Doyle and Snyder (1999), who find that firms in the automotive industry appear to have an incentive to share demand information with their competitors.

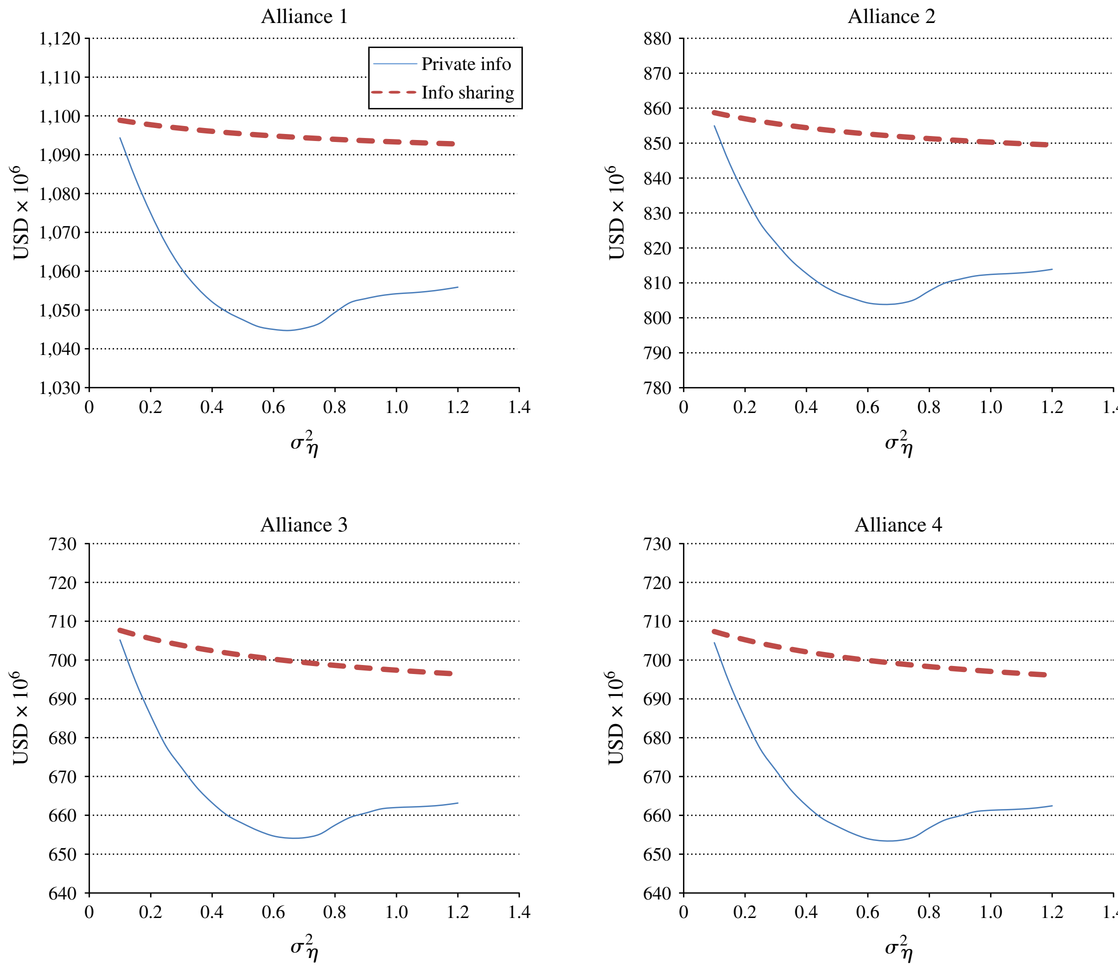
Noticing that firms only care about the signal-to-noise ratio of the demand information also allows

[23] An analytical proof of this case is provided in Web Appendix 2.

[24] The analysis does not consider coalitional information sharing. In that case, each firm could decide to share information with only a few of its competitors. This setting is complicated by the number of possible sharing combinations and, as a result, the computational power required to analyze them.

[25] Alternatively, the program can also be solved at each draw of a simulated vector s_t separately, without interpolation.

Figure 7 (Color online) Operating Profits in Information Sharing Scenarios



us to apply these findings to situations where market volatility changes but the variance of the demand signals remains constant. Our findings suggest that, ceteris paribus, firms have little to gain from exchanging information in very stable or extremely volatile markets. However, firms benefit from sharing information when markets have intermediate levels of volatility.

The profitability analysis suggests two additional questions: First, as in the present example, some industries suffer from high profit variability (e.g., semiconductors, airlines), which leads some governments to protect the players by introducing variance-decreasing measures. Although the analysis above suggests governments should allow DRAM firms to share demand information if they want to increase their profits, in some cases this change could hurt the industry if the result is higher payoff variability and higher risk of bankruptcy. Hence, it is worth investigating how profit variability is affected by information sharing. Second, it is also interesting to consider the extent to which the increase in profits is sourced from consumer surplus. If the downstream industry profits and consumer welfare are being penalized in excess of the benefits to firms, allowing for information sharing may become an undesirable policy.

5.3. Information Sharing and Profit Variability

Predicting the effect of information sharing on profit variability a priori is challenging. On one hand, with better information firms make more accurate decisions, possibly leading the variability of their profits to decrease. On the other hand, an increase in the correlation of actions may also increase the variance of profits, because each firm's action can no longer be compensated by the actions of its competitors. For example, before sharing information, one firm's bad decision of adding too much capacity could be compensated by its rival's decision of adding too little. In this case, the market price and firm profits could stay relatively stable. Once firms share demand information however, their actions become more correlated and it is possible that payoff variability increases.

The variability of profits is plotted in Figure 8 at different levels of parameter σ_η^2. It is clear that allowing for information sharing not only increases firm

Figure 8 (Color online) Standard Deviation of Industry Profits

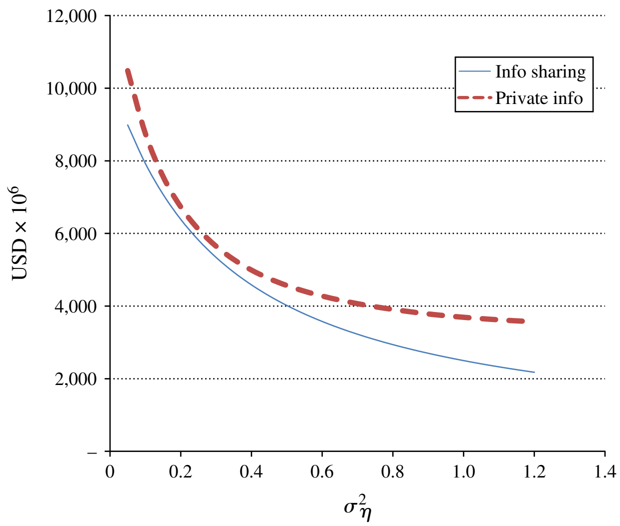
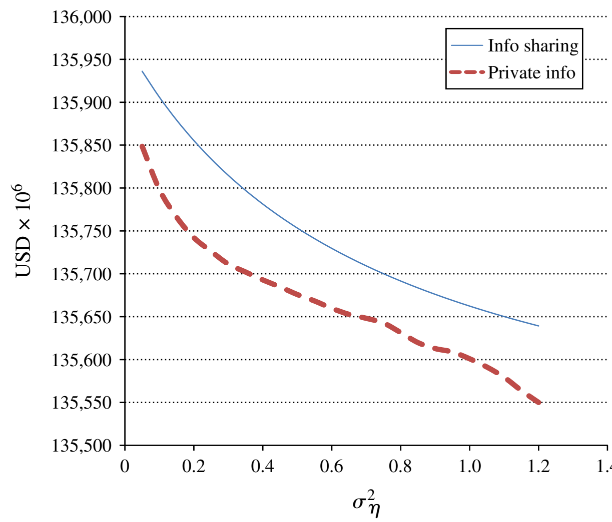


Figure 9 (Color online) Expected Consumer Surplus in Information Sharing Scenarios



profits but also decreases payoff variability. Hence, one should expect a more stable industry when information sharing about demand is allowed. Given that bankruptcy is often associated with the variance of payoffs, promoting credible information sharing may indeed decrease the risk of bankruptcy for industries.[26]

5.4. Consumer Welfare

In general, policies implemented upstream have an effect on downstream profits as well as on consumer surplus. If the total surplus were fixed, an increase in DRAM profits would have negative effects on consumer welfare. However, this assessment ignores that sharing information can lead firms to coordinate their decisions with the market preferences. Hence, it is possible that consumer welfare increases with information sharing. We now look at the impact of allowing information sharing on consumer surplus.[27]

The expected consumer surplus is given by

$$\int_0^{\infty}\left\{\int_0^{Q^*(\varepsilon)} p(s)ds - p(Q^*(\varepsilon))Q^*(\varepsilon)\right\} dF(\varepsilon), \tag{14}$$

where $F(\varepsilon)$ is the cumulative distribution function of the demand shocks.[28] The inner integral provides the consumer surplus for a given shock ε, whereas the outer integral yields the average consumer surplus. The results across different values of σ_η^2 are provided in Figure 9. Information sharing has a positive effect on consumer surplus across all values of the signal precision. The rationale for this is that by sharing information, firms coordinate their actions to the market needs better.

In conjunction with the previous analyses, this result is striking because it indicates that all agents benefit from allowing firms to share information with their competitors. However, it is important to note that the results are not generalizable to all capacity/quantity competition settings. Given their novelty, they instead suggest that our previous understanding of the consequences of information sharing is not always readily applicable and that the consequences of this type of regulation need to be considered on a case-by-case basis.

6. Concluding Remarks

Demand information is a fundamental component for decision making in competition settings. This is especially true in industries where decisions are made in advance of actual demand conditions being realized. This paper takes the example of the DRAM industry. It presents a model that allows firms to set up capacity and production levels and consider what the likely information of their competitors is. It also provides identification arguments and proposes a method to solve the equilibrium and estimate the fundamental parameters. By ex post recovering the demand shocks, the estimation identifies the most likely parameters underlying the firms' decisions. By comparing the expected model predictions with the actual decisions in the data, it is possible to recover the demand signals and estimate the quality of the information available to firms.

[26] See, for example, Oprea (2014) and the discussions therein.

[27] Because consumer surplus is an upper bound for end-consumer welfare, it is also often used in regulatory procedures.

[28] The expression for the expected consumer surplus is abbreviated for simplicity. In fact, the function Q^* depends on the capacity levels chosen by firms, which in turn depend on their demand signals (which may or may not be shared across firms).

We recover nonmonotonic best-response curves, which mostly derive from the curvature of the market demand function. When the best response is nonmonotonic, the available theoretical results are not immediately applicable, and empirical analysis becomes especially relevant. The counterfactual analyses show that whether the quality of information is good or bad for firms depends on their level of installed capacity. In particular, better information may decrease operational profits when capacity is likely to bind because when information quality is high, firms would like to increase production significantly when they receive good news. However, if a firm faces a low level of capacity, it cannot take advantage of the good news and is hurt by the resulting lower market price, driven by the actions of its competitors.

When the capacity decisions are endogenous, we find that firms benefit from information sharing. This result expands the information sharing literature by demonstrating that firms can benefit from sharing information in quantity-setting contexts. The immediate implication is that understanding the consequences of allowing firms to share information requires a case-by-case analysis, and overarching statements may be imprecise. It is worth considering whether the result of the DRAM manufacturing industry informs us of other settings. The previous literature has described the case where price decreases linearly with output. However, in the DRAM industry, price decreases slower. Managerial interviews suggest that the main explanation is that original equipment manufacturers (OEMs) are able to reconfigure their products to respond to spikes in supply in a relatively short period of time. Hence, in times of oversupply, OEMs reconfigure their offerings to accommodate more memory, leading prices to decrease slower than if oversupply could not be absorbed by the market. That prices reduce slowly enough leads to nonmonotonic best-response curves in competition, which in turn produces our main result. As a heuristic rule, industries higher in the value chain are more likely to benefit from information sharing because their output can be reconfigured downstream (e.g., raw materials in the extreme case). Finally, we also find that as firms anticipate demand shocks better, payoffs become more stable with information sharing. This result is especially relevant in industries where firm exit is relatively frequent. Governments seeking to protect firms may consider allowing information sharing as a means to smooth industry instabilities. Our final result is that consumers may also benefit from information sharing. This happens because when firms share information, they coordinate decisions with the market needs better.

Whereas this paper has focused on the case of overlapping repeated interactions, it is possible that the case of competition with capacity adjustment costs reveals new insights. We conjecture that information sharing may become less valuable in that case because in the presence of adjustment costs, firms invest more in capacity to keep the option value of producing more both today and tomorrow open. It follows that the same amount of demand information obtained through sharing becomes less valuable because of the "stickiness" in capacity levels. However, a full analysis is likely to reveal additional insights. Other future research avenues include endogenizing the data gathering efforts by firms. For example, when firms decide data gathering efforts, they should take into account the fact that their data will be later supplemented by their rivals' data through sharing. This may generate a free-riding problem in information acquisition efforts that may be influenced by firm entry and exit, but the precise outcomes are currently unknown. Finally, allowing firms to signal their types through capacity investments is challenging but would be useful to characterize novel information sharing patterns.

Supplemental Material

Supplemental material to this paper is available at https://doi.org/10.1287/mnsc.2015.2297.

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Appendix A. The Firm's Dynamic Problem with Additively Separable Investment Costs

In this section we show that the repeated-game formulation is consistent with an infinite-horizon one with a precise interpretation. It is useful to consider a simple example in which a single agent earns payoffs according to the Bellman equation:

$$W(s_t) = \max_{x_t}\left\{\pi(s_t) + \omega_2(s_t - x_t) + \delta E[W(s_{t+1}) \mid x_t, s_t]\right\}, \quad \text{(A1)}$$

where $\pi(\cdot)$ is a per-period profit function that depends on state variable s_t, and $\omega_2(s_t - x_t)$ is an adjustment cost, also influencing the period's payoffs. It suffices that the adjustment cost is additively separable and symmetric, as we show below.[29] Variable x_t is the firm's control, which affects the state variable through transition $s_{t+1} = x_t$. Because of this, the firm's decision affects its present as well as its future payoffs. Given the transition function above, we can rewrite the firm's problem as

$$\begin{aligned} W(s_t) &= \max_{x_t}\{\pi(s_t) + \omega_2(s_t - x_t) + \delta E[W(s_{t+1}) \mid x_t, s_t]\} \\ &= \pi(s_t) + \omega_2 s_t + \max_{x_t}\{-\omega_2 x_t + \delta E[W(s_{t+1}) \mid x_t, s_t]\} \\ &= \pi(s_t) + \omega_2 s_t \\ &\quad + \max_{x_t}\Big\{-\omega_2 x_t + \delta E\Big[\max_{x_{t+1}}\Big\{\pi(s_{t+1}) + \omega_2(s_{t+1} - x_{t+1}) \\ &\qquad + \delta E\big[W(s_{t+2}) \mid x_{t+1}, s_{t+1}\big]\Big\} \Big| x_t, s_t\Big]\Big\}. \end{aligned}$$

The second equality arises from the fact that at time t, $\pi(s_t)$ is sunk because x_t can no longer influence it. This is due to the transition function

$$\frac{\partial s_t}{\partial x_\tau} = \begin{cases} 1 & t+1 = \tau, \\ 0 & \text{otherwise.} \end{cases}$$

The third equality expands the expression by substituting in the next period's payoffs. As before, we can extract elements from the $\max_{x_{t+1}}$ operator. This yields

$$\begin{aligned} &W(s_t) \\ &= \pi(s_t) + \omega_2 s_t + \max_{x_t}\Big\{-\omega_2 x_t + \delta\pi(x_t) + \delta\omega_2 x_t \\ &\quad + \delta E\Big[\max_{x_{t+1}}\{-\omega_2 x_{t+1} + \delta E[W(s_{t+2}) \mid x_{t+1}, s_{t+1}]\} \Big| x_t, s_t\Big]\Big\}. \quad \text{(A2)} \end{aligned}$$

Define $V(s_t) \equiv W(s_t) - \pi(s_t) - \omega_2 s_t$ and substitute into (A2) to get

$$\begin{aligned} V(s_t) &= \max_{x_t}\Big\{\delta\pi(x_t) - \omega_2(1-\delta)x_t \\ &\quad + \delta E\Big[\underbrace{\max_{x_{t+1}}\{\delta\pi(x_{t+1}) - \omega_2(1-\delta)x_{t+1} + \delta E[V(s_{t+2}) \mid x_{t+1}, s_{t+1}]\}}_{V(s_{t+1})} \Big| x_t, s_t\Big]\Big\} \\ V(s_t) &= \max_{x_t}\{\delta\pi(x_t) - \omega_2(1-\delta)x_t + \delta E[V(s_{t+1}) \mid x_t, s_t]\}. \end{aligned}$$

Note that s_t does not enter the instantaneous payoff function $\delta\pi(x_t) - \omega_2(1-\delta)x_t$. The reason for this is that we gathered all of the state variables' future effects on a single period by applying appropriate discounting. It follows that the dynamic problem can be recast into a series of repeated one-period problems. To see this, note that $V(s_t) = \bar{V}$, where $\bar{V}$ is a constant. To find the firm's optimal policy $\{x_t^*\}_{t=1}^{\infty}$, it suffices to solve the series of problems

$$x_t^* = \arg\max_{x_t}\{\delta\pi(x_t) - \omega_2(1-\delta)x_t\} \quad \text{(A3)}$$

for each period.

This result relies heavily on the use of the MPE concept. In particular, we focus on equilibria where firms restrict themselves to using payoff-relevant state variables to make decisions. This is the standard assumption in the empirical dynamic literature, and more complicated equilibria are usually the domain of the repeated games literature.

We now apply analogous steps to derive the implications of the additive separability assumption to our model. Here, we consider the case in which at time t firm i decides on a production plan y_{it}, which yields the corresponding production output q_{it+1} in the next period, such that $q_{it+1} = y_{it}$.[30] Hence, y_{it} is a control variable (production plan at time t) and q_{it+1} is a state variable (production available at time $t+1$). Each firm also decides on its capacity plans. At time t firm i chooses capacity plan κ_{it}. This yields capacity level K_{it+1} in period $t+1$. Similar to production, κ_{it} is a control variable and the resulting capacity, K_{it+1}, is a state variable. Hence, at time t, firm i decides on production and capacity plans y_{it} and κ_{it}, respectively. The transition functions are given by $q_{it+1} = y_{it}$ and $K_{it+1} = \kappa_{it}$. Moreover, in each period the firm's production is constrained by the capacity it has available; i.e., $y_{it} \le K_{it}$, $\forall t$.

We now show that under the maintained assumptions the firm's problem is equivalent to a repeated two-period problem. We first focus on the production problem because it carries no dynamic effects for the firms other than next period's operating profits. At time t, firm i chooses its production plan y_{it} by solving

$$\begin{aligned} \max_{y_{it}} \quad & \{\delta E_{\varepsilon_{t+1}}[\pi_i(q_{it+1}, q_{-it+1}, \varepsilon_{t+1}) \mid K_t, s_{t+1}]\} \\ \text{s.t.} \quad & y_{it} \le K_{it}, \\ & q_{it+1} = y_{it}. \end{aligned}$$

The firm takes the capacity levels K_t, the demand signals s_{t+1}, and the production transition functions into account. Denote $\delta\pi_i^*(K_t, s_{t+1})$ as the firm's expected discounted operating payoffs at time t conditional on the available capacity levels K_t and market information s_{t+1}.[31] It is useful to note that capacity plan κ_{it} only affects operating profits directly in two periods' time. The reason is that κ_{it} generates capacity K_{it+1}, which at time $t+1$ is used for production plan y_{it+1}. This plan in turn generates q_{it+2} units to be taken to the market at time $t+2$. Hence, production plan κ_{it} is irrelevant for *operating* profits at times t and $t+1$.

Consider now the Bellman equation below, which separates present and future payoffs for firm i:

$$\begin{aligned} W_i(\Omega_{it}) = \max_{\kappa_{it}}\{&\pi_i^*(K_{t-1}, s_t) - \tilde{\omega}_2(\kappa_{it}^2 - \phi K_{it}^2) \\ &+ \delta E_{\Omega_{it+1}}(W_i(\Omega_{it+1}) \mid \kappa_{it}, \Omega_{it})\}, \end{aligned} \quad \text{(A4)}$$

where Ω_{it} is the set of known and relevant state variables for firm i at time t, defined as $\Omega_{it} \equiv \{s_t, s_{t+1}, s_{it+2}, K_{t-1}, K_t\}$, and $\tilde{\omega}_2(\kappa_{it}^2 - \phi K_{it}^2)$ is a functional form used to capture local

[29] By *symmetric* we mean that adjustment costs are constant, independently of the direction of the adjustment.

[30] It is trivial to consider the case where production is instantaneous. Here, we show the proof for the more complicated case where both capacity *and* production plans require a period to be implemented.

[31] Note that production costs are exactly known to firms, as well as their transitions. In this sense, they are equivalent to model parameters and are omitted for notation simplicity.

adjustment costs to capacity. This specification captures the idea that capacity may depreciate according to parameter ϕ.

Just as in the example above, the payoffs $\pi_i^*(K_{t-1}, s_t) - \tilde{\omega}_2\phi K_{it}^2$ are sunk at time t and irrelevant for decision κ_{it}. Hence, expression (A4) is equal to

$$W_i(\Omega_{it}) = \pi_i^*(K_{t-1}, s_t) + \tilde{\omega}_2\phi K_{it}^2 + \max_{\kappa_{it}}\{-\tilde{\omega}_2\kappa_{it}^2 + \delta E_{\Omega_{it+1}}(W_i(\Omega_{it+1}) \mid \kappa_{it}, \Omega_{it})\}. \quad \text{(A5)}$$

Expanding the expectation operator yields

$$\begin{aligned} W_i(\Omega_{it}) &= \pi_i^*(K_{t-1}, s_t) + \tilde{\omega}_2\phi K_{it}^2 \\ &\quad + \max_{\kappa_{it}}\Big\{-\tilde{\omega}_2\kappa_{it}^2 + \delta E_{\Omega_{it+1}}\Big(\pi_i^*(K_t, s_{t+1}) + \tilde{\omega}_2\phi K_{it+1}^2 \\ &\qquad + \max_{\kappa_{it+1}}\{-\tilde{\omega}_2\kappa_{it+1}^2 + \delta E_{\Omega_{it+2}}(W_i(\Omega_{it+2}) \mid \kappa_{it+1}, \\ &\qquad\qquad \Omega_{it+1})\}\Big| \kappa_{it}, \Omega_{it}\Big)\Big\} \\ &= \pi_i^*(K_{t-1}, s_t) + \tilde{\omega}_2\phi K_{it}^2 + \delta\pi_i^*(K_t, s_{t+1}) \\ &\quad + \max_{\kappa_{it}}\Big\{-\tilde{\omega}_2(1-\delta\phi)\kappa_{it}^2 + \delta E_{\Omega_{it+1}}\Big(\max_{\kappa_{it+1}}\{-\tilde{\omega}_2\kappa_{it+1}^2 \\ &\qquad + \delta E_{\Omega_{it+2}}(W_i(\Omega_{it+2}) \mid \kappa_{it+1}, \Omega_{it+1})\}\Big| \kappa_{it}, \Omega_{it}\Big)\Big\}. \end{aligned}$$

Now, define $V_i(\Omega_{it}) \equiv W_i(\Omega_{it}) - \pi_i^*(K_{t-1}, s_t) - \tilde{\omega}_2\phi K_{it}^2 - \delta\pi_i^*(K_t, s_{t+1})$ and substitute into the equality above to get

$$\begin{aligned} V_i(\Omega_{it}) &= \max_{\kappa_{it}}\Big\{-\tilde{\omega}_2(1-\phi\delta)\kappa_{it}^2 \\ &\quad + \delta E_{\Omega_{it+1}}\Big(\max_{\kappa_{it+1}}\{-\tilde{\omega}_2\kappa_{it+1}^2 \\ &\quad + \delta E_{\Omega_{it+2}}(V_i(\Omega_{it+2}) + \pi_i^*(K_{t+1}, s_{t+2}) + \tilde{\omega}_2\phi K_{it+2}^2 \\ &\quad + \delta\pi_i^*(K_{t+2}, s_{t+3}) \mid \kappa_{it+1}, \Omega_{it+1})\} \Big| \kappa_{it}, \Omega_{it}\Big)\Big\} \\ &= \max_{\kappa_{it}}\{\delta^2 E[\pi_i^*(\kappa_t, s_{t+2}) \mid s_{it+2}] - \tilde{\omega}_2(1-\phi\delta)\kappa_{it}^2 \\ &\qquad + \delta E_{\Omega_{it+1}}(V_i(\Omega_{it+1}) \mid \kappa_{it}, \Omega_{it})\}. \end{aligned} \quad \text{(A6)}$$

where

$$V_i(\Omega_{it+1}) = \max_{\kappa_{it+1}}\{\delta^2 E[\pi_i^*(\kappa_{t+1}, s_{t+3}) \mid s_{it+3}] - \tilde{\omega}_2(1-\phi\delta)\kappa_{it+1}^2 + \delta E_{\Omega_{it+2}}(V_i(\Omega_{it+2}) \mid \kappa_{it+1}, \Omega_{it+1})\}.$$

By inspecting the expression for the period's discounted payoff $\delta^2 E[\pi_i^*(\kappa_t, s_{t+2}) \mid s_{it+2}] - \tilde{\omega}_2(1-\phi\delta)\kappa_{it}^2$, we note that only state variable s_{it+2} is payoff relevant for firm i. It follows that the firms' problem can be reduced to solving a series of capacity (and production) plans given the demand information s_{it+2}. Note that solving for the capacity plan κ_{it} entails solving a nested production planning problem y_{it+1}, so that our result yields a two-period overlapping repeated game. The separation result does not depend on the assumption that the demand signals are independently distributed over time: it suffices that their transitions are additively separable over time.[32] Finally, the cost associated with adding capacity ω_2 is not separately identifiable from the depreciation $(1-\phi\delta)$.

[32] A proof is available from the author.

Appendix B. Estimation Steps

Instead of solving the firms' first-order conditions at all possible levels of the demand signals, we select a subset of points in the support of s_{it}, and the capacity policies $K_{it}(s_{it})$, $i = 1..n$ are replaced by parameterized cubic splines.[33] The capacity policies of firms are recovered as follows: First, fix a guess for the model parameters. Let $\{s_{it}\}^{r_1}$, $r_1 = 1..R_1$ be the set of approximation points (constant across firms) in the domain of the policy function $K_{it}(s_{it})$.[34] For each firm and each point $s_{it}^{r_1}$, define quadrature nodes $\{s_{jt} \mid s_{it}^{r_1}\}^{r_2}$, $r_2 = 1..R_2$, which will help calculate the outer expectation of expression (10). Finally, solve the set of capacity first-order conditions for all firms at each of the domain points with respect to the firms' spline parameters. The solution of this system recovers the set of the policy functions $K_{it}^*(s_{it})$, $i = 1..n$ at the current guess of the model parameters.

For each guess of the spline parameters, one is required to solve the quantity subgame multiple times. To reduce estimation time, fifth-degree Gauss–Hermite monomial quadratures were used to calculate the outer expectations. The outer quadrature for the conditional expectation using $\{s_{jt} \mid s_{it}^{r_1}\}^{r_2}$ is formed by 15 points.[35] The procedure above solves a system of $n \times R_1 = 4 \times 5 = 20$ capacity first-order conditions, for each guess of the structural parameters. Evaluating each condition entails solving the underlying quantity equilibrium *finite diff.* $\times R_2 = 2 \times 15 = 30$ times (each of which yields 1 of 81 possible solutions). Hence, a single evaluation of the system of capacity first-order conditions requires solving the underlying quantity game 600 times.

First Stage: Demand Parameter Estimation

- Use Moore's law and its powers as demand instruments.
- Construct demand moments.
- Implement the VARHAC procedure to generate a consistent covariance estimator of the demand moments in the presence of heteroskedastic error terms.
- Estimate the parameters μ, β, λ, σ_ε^2 as well as their asymptotic variance by minimizing the generalized method of moments criterion function.

Second Stage: Firm Parameter Estimation

Quantity moments: $E_t[Q_t^l - \hat{Q}_t^{*l}]$, $l = 1..2$:

- Draw simulations of $\sum_{i\in n} \log(s_{it}) \mid \hat{\varepsilon}_t$. At each time period and for each simulation, calculate the object $E_{\varepsilon_t}[\varepsilon_t \mid s_t]$, which goes into the Kuhn–Tucker conditions for firms.
- Solve the Kuhn–Tucker conditions for each node, given the capacity levels in the data.

[33] Galerkin-related methods, as proposed by Judd (1998), can also be used to solve the system of continuous equations, but performed poorly in our setting.

[34] Those points are located at the Chebyshev nodes to maximize the stability of the approximation to the policy functions. A wide domain (0.5, 10.0) was used to reduce the need for extrapolation. A number of sensitivity tests were performed around these values with little impact.

[35] Quadratures performed extremely well when compared to the results of simulation and allowed for much faster execution. In addition, derivative-based search methods were used: estimation time increased but accuracy improved greatly.

- Average equilibrium quantities using the quadrature rule to calculate $E_{s_t \mid \hat{\varepsilon}_t}[q_{it}^*]$ and sum over firms in order to generate $\hat{Q}_t^*$. Apply the second power before averaging to get the second moment.

Capacity moments: e.g., $E_t[K_t^l - \hat{K}_t^{*l}]$, $l = 1..2$:

- Start with a guess for the equilibrium capacity policy function for each firm and each observation captured by spline $K(s_{it})$, with D control points (Chebyshev nodes), denoted by x^d.
- Create a three-dimensional quadrature for each control abscissa, indexed by r_1, $\log(s_{-it})^{r_2} \mid s_{it}^{r_1}$, $d_1 = 1..49$.
- Calculate $E_{\varepsilon_t}[\varepsilon_t \mid \sum_{i \in n} \log(s_{it}^{r_1, r_2})]$ for each set of quadrature nodes above to solve the quantity game for the nodes above. Store profits in matrices Π_{r_1, r_2}^i, $i = 1..n$.
- Recalculate the spline for each control point x^d such that $K(s_{it})$ becomes $K(s_{it}) + h$, where $h = 1e - 6$, and recalculate firm profits for all nodes. Build profit matrices $\Pi_{r_1, r_2}^{\prime i}$, $i = 1..n$.
- Calculate the marginal benefit of increasing capacity at each node for firm i by h, given by$(\Pi_{r_1, r_2}^{\prime i} - \Pi_{r_1, r_2}^i)/h$. Add the cost of adding capacity to the expression above, using the parameter guess for ω_2.
- Perform expectations of payoffs above across nodes r_2 so as to get the capacity first-order conditions for each firm.
- Update spline parameters for each firm until the first-order conditions equal zero.
- Average splines over nodes r_1 to calculate the predicted expected equilibrium policy $\hat{K}_{it}^{*l} = E[K_{it}(s_{it}^{r_1})^l \mid \hat{\varepsilon}_{it}]$.
- Build all moment conditions and iterate over guesses of parameters ω_0, ω_1, ω_2, σ_η^2.

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