Collusion Along the Learning Curve:  
Theory and Evidence from the Semiconductor Industry

by

Danial Asmat

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*Economic Analysis Group, Antitrust Division, U.S. Department of Justice, danial.asmat@usdoj.gov. The views expressed in this paper are those of the authors and are not purported to reflect the views of the U.S. Department of Justice. The empirical methodology for this article was constructed with the aid of publicly available media and academic sources while the author was a Ph.D. student at the University of Michigan, prior to any employment with the U.S. Department of Justice. The views expressed are not purported to reflect those of the U.S. Department of Justice.
Collusion Along the Learning Curve:

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Danial Asmat*

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Abstract

This paper formulates a theory of collusion with learning-by-doing and multiproduct competition and tests it with data from an explicit cartel. The model shows that collusion is harder to sustain on a new product generation, where learning is high, than an old generation, where learning is low. Collusion on the old generation shifts demand toward the new generation, raising its output. Empirical analysis exploits variation between cartelization and competition in the DRAM market to identify counterfactual quantities and prices. Consistent with the model, cartel firms cut output of older generations by up to 50% and increased output of newer generations manifold.

JEL Classification: D43, L13, L41, L63

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1 Introduction

Since the turn of the century, cartels discovered in multibillion dollar high-technology markets have resulted in several of the largest antitrust fines in U.S. history.\(^1\) Global manufacturers of LCD panels, cathode ray tubes, optical disk drives, and three different types of memory chips have settled criminal or civil claims for price fixing. These markets feature several characteristics long known to enable collusion, among them product homogeneity, cooperative research and development, and high barriers to entry. Yet they also share two additional characteristics. First, manufacturing displays learning-by-doing: a firm’s cumulative output reduces the marginal cost of its future output. Second, firms steadily release new product generations based on technological advancements, such as those predicted by Moore’s Law. Multiple product generations therefore overlap at the same time on the market.\(^2\)

The discovery of such cartels raises a natural question: what is the impact of learning-by-doing on the damage attributable to collusion? Collusion is well understood to generate inefficiency by raising price above marginal cost. At first glance, learning raises this inefficiency: by restricting output, firms forfeit some of the gains to learning and inhibit cost reduction. This paper’s contribution is to highlight that collusive equilibria in high-technology markets are determined by the rate at which firms learn and the possibility of multiproduct demand linkage. It develops a repeated game model of learning with multiproduct competition to generate testable predictions of collusion in such markets. It then uses data from an illegal price fixing cartel in the Dynamic Random Access Memory (DRAM) market to find evidence consistent with both the theory and its mechanism.

The model builds two insights in succession. First, collusion is more likely to be successful in an older product generation than in a newer generation. This is because firms learn more early in the product life cycle than later. The more that firms have to learn, the lower is their future cost as a function of their current output. The more they can reduce their future cost, the weaker is a punishment from defecting from a collusive strategy, and the higher is the minimum discount factor necessary to enforce a collusive strategy.

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\(^1\)AU Optronics, LG Display, and Samsung Electronics have each received penalties of $300 million or more since 2006. AU Optronics’ $500 million fine is the largest Sherman Act corporate fine to date; see [http://www.justice.gov/atr/public/criminal/sherman10.html](http://www.justice.gov/atr/public/criminal/sherman10.html).

\(^2\)In 2014, for example, buyers could choose between 2Gb, 4Gb and other generations of chips. See [http://www.forbes.com/sites/jimhandy/2014/06/27/dram-asps-soften-is-that-important/](http://www.forbes.com/sites/jimhandy/2014/06/27/dram-asps-soften-is-that-important/).
Second, successful collusion in the older generation shifts demand to the newer generation, which is an imperfect substitute. If firms are unable to collude on the newer generation, then they sell more of its units than they would under uniform competition on both generations. If firms sell more units in one period, then they learn more in that period, and they reduce their marginal cost further in subsequent periods. Counterintuitively, collusion on the older product then increases the accrued learning in the newer product.

DRAM presents an ideal application for several reasons. The product’s explosive innovation has helped fuel the computer and electronics revolution, making it a critical part of the world’s economy. DRAM production is a classic example of learning-by-doing: output allows firms to reduce cost-per-chip by reducing the rate of defective chips in manufacturing. Moreover, chip generations are released every two to three years, and the learning process repeats with each new generation. Because the product life cycle is several years, multiple generations overlap at any given time.

These three features—collusion, learning, and multiproduct competition—allow the model to be naturally tested. I employ firm-level data on the DRAM market before, during, and after dates of admitted cartel activity. I estimate changes in firm-level outputs and generation-level prices attributable to the cartel, separately for five DRAM generations. I identify the change attributable to the cartel by exploiting variation between cartel and non-cartel time periods as well as variation in the stage of the product life cycle during the cartel time period.

Empirical results are strikingly consistent with the model’s predictions. In the two most mature cartel generations, 4Mb and 16Mb, I estimate that firms have reduced their output by up to 50% relative to the competitive benchmark. Among newer 64Mb, 128Mb, and 256Mb generations, on the other hand, firms are estimated to have increased their output manifold, consistent with a demand shift toward frontier generations. Estimates of the cartel price effect are positive and as high as as about 20% among 4Mb and 16Mb, consistent with successful collusion. Price estimates for the newer generations are negative and as low as about 70%, consistent with the demand shift and faster accrued learning. Results are robust to variation in industry-wide capacity levels and heterogeneity in underlying DRAM technology. Overall, because of the

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3 Dates are based on publicly available litigation evidence from the Department of Justice (DOJ), European Commission (EC), and Noll (2014).
differential success of collusion across generations and the resulting demand shift to the frontier, the cartel led to damages on older generations and possible gains on newer generations.

This paper bridges a gap between two distinct groups of research in industrial organization: learning-by-doing and collusion. It contributes to both theory and empirical evidence in each of these two areas. It extends the theory of oligopolistic competition with learning to include the possibility of tacit or explicit coordination. Similarly, it adds learning within a realistic multiproduct setting to standard models of repeated game collusion. Empirically, it extends literature on the learning-intensive semiconductor industry as it enters an era of increased concentration, intellectual property disputes and antitrust scrutiny. It also joins empirical literature that studies a “hard core” price fixing cartel to assess how firms reach incentive compatibility in collusive equilibria, which is otherwise difficult to assess.

The model of learning-by-doing is closest to Siebert (2010) and Fudenberg and Tirole (1983): firms choose quantities of one product in a learning period knowing that they gain a cost reduction as a function of output in a post-learning period. Product generations are imperfect substitutes for one another. The model is embedded within an infinite horizon game, as in Cabral and Riordan (1994) and Besanko et al. (2010). It differs from existing models of learning-by-doing in focusing on collusive equilibria rather than long-run industry dynamics such as increasing dominance, natural monopoly and predatory pricing.

The model’s fundamental contribution is to show how learning-by-doing can induce firms to collude in one product market while competing in another product market. This adds to literature on “semi-collusion,” in which firms collude along one dimension but compete along another dimension (See Benoit and Krishna, 1987, Davidson and Deneckere, 1990, and Compte, Jenny and Rey, 2002 for capacity; Brod and Shivakumar, 1999 and Fershtman and Pakes, 2000 for R&D and product differentiation). The model’s secondary contribution is to illustrate that collusion in one product generation shifts demand to a newer product generation, which can create more sales and hence more learning opportunities relative to competition. Like other papers in

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4The Cournot framework is apt because capacity for semiconductors and other high-technology products is fixed within a product life cycle. Other quantity-setting models of learning include Spence (1981), Ghemawat and Spence (1985), Dasgupta and Stiglitz (1988) and Cabral and Riordan (1997).

5Mookherjee and Ray (1991) propose a model of collusion with scale economies and learning-by-doing. I expand on their results by adding demand linkages between product generations in a quantity-setting framework, which characterize numerous high-technology industries with capacity constraints.

6See also de Roos (2004) and Fagart (2016) for models of collusion with dynamic investment more generally.
this literature, it shows that semi-collusion can change equilibrium outcomes to offset some of the welfare loss attributable to collusion.

The empirical analysis adds to a number of studies that test the theory of oligopolistic competition with learning using empirical data from the semiconductor industry. Irwin and Klenow (1994) specify a quantity-setting model to estimate that a firm’s marginal cost of chip production is reduced by an average of 20% following a 100% increase in output, but that there is no significant learning effect between new product generations. Zulehner (2003) and Siebert and Zulehner (2013) examine the rate of learning and competitiveness in DRAM using data from the 1970s to the mid-1990s, before firms began explicitly colluding. Gardete (Forthcoming) uses more recent data to estimate a structural model of imperfect information and finds that DRAM manufacturers share demand information in equilibrium.

Finally, this paper contributes to empirical evidence of how cartels meet collusive incentive compatibility constraints (Levenstein, 1997; Scott Morton, 1997; Genesove and Mullin, 2001; Roller and Steen, 2006; Mariuzzo and Walsh, 2013; and Clark and Houde, 2013, 2014). By accounting for learning-by-doing and multiproduct competition, it generates a new link between industry features, cartel sustainability, and damages. It remains vital to understand the viability collusion using data from modern cartels like DRAM, which operate in vastly different legal and technological settings from those in the past.

The remainder of the paper is outlined as follows. Section 2 presents a multi-period, infinite horizon model of collusion over the product life cycle and generates testable predictions for a change from competition to collusion. Section 3 and Section 4 describe the features of the industry, the cartel, and the data. Section 5 estimates output and price effects attributable to the cartel between generations. I conclude in Section 6 by discussing the results and implications for antitrust policy.

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7 Several additional studies have found evidence consistent with significant learning effects in DRAM and other memory chips. See Dick (1991), Nye (1996), Gruber (1998), and Cabral and Leiblein (2001).
8 The role of memory and microprocessor chips, as well as technology standards in memory chips, is explained in Section 3.
9 See Levenstein and Suslow (2006) for a broader review of empirical literature examining incentive compatibility in cartels.
2 Theoretical Model

2.1 Preliminaries

I embed a discrete time model of learning based on Siebert (2010) and Fudenberg and Tirole (1983) into an infinitely-repeated duopoly game. To overcome the analytical challenges inherent in computing supra-competitive equilibria within a dynamic game, the model imposes supply-side structure on the evolution of costs, the timing of entry, and the type of collusive strategies played. It compresses several years of rapid firm learning into one period, and several additional years of slower learning into a second period. This framework simplifies the dynamic game into a tractable model while preserving the key feature of learning: a firm’s future cost reduction is more sensitive to its output early in the product life cycle than later. The intuition of results would be identical in a multi-period learning model as long as the speed of learning strictly decreases over time.

Similarly, the model assumes that firms choose quantities, which captures the capacity-pricing nature of the market without explicitly modeling capacity decisions in a separate stage. Explicitly generating results in a price-setting game without fixed capacity would be of limited insight due to the inherent difficulty of sustaining collusion in such a framework.

Two firms, $i$ and $j$, produce two products $old$ and $new$, indexed by $k \in \{o,n\}$. The game has three phases, and product $n$ enters exogenously one phase after product $o$’s entry. The supply side of the game is depicted visually in fig. 1.

Learning occurs between the game’s first and second phases: marginal cost declines from $c_1$ to $c_1 \cdot f(q_{ikt-1})$, where $f(0) = 1$, $\frac{\partial f}{\partial q} < 0$, $\frac{\partial^2 f}{\partial q^2} > 0$, $\lim_{q \to \infty} f(q) = \frac{c}{c_1}$, and $0 < \frac{c}{c_1} < 1$. Between the second and third phases, any further learning effects diffuse to both firms, so that marginal cost reaches its minimum $c$.

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Kreps and Scheinkman (1983) show that static equilibria from a quantity game with one period are equivalent to those from a capacity-pricing game with two periods, under plausible technical conditions.

Entry is assumed exogenous to focus on firms’ strategic incentives to collude once they have entered a generation. The data show that major DRAM manufacturers generally enter each generation within one year of each other.

The learning curve is identical between firms $i$ and $j$, and learning occurs only within generations. This is consistent with empirical evidence (e.g. Irwin and Klenow (1994)) as well as the Siebert (2010) and Zulehner (2003) models.
From phase three onward, firms play a static Cournot game with identical costs. Profits are discounted at a common rate $\delta \in (0, 1)$ per period.

Firms compete in quantities and face demand for products that are imperfect substitutes. They simultaneously select quantities $q_{ikt}$ at the start of each period, and the total quantity $Q_{kt}$ determines the market-clearing price $P_{kt}$. After each period and before the next, firms observe the quantity decision of their rival with perfect information.  

Inverse demand is given by $P(Q_{ot},Q_{nt})$, $P : \mathbb{R}^{2} \mapsto \mathbb{R}^{2}$, with $\frac{\partial P_{kt}}{\partial q_{kt}} < 0$ and $\frac{\partial P_{kt}}{\partial q_{-kt}} < 0$. Assume that demand is identical for all periods $t$, and that demand is symmetric between products $o$ and $n$. It will be convenient in some cases to assume that demand is log-linear, so that it has the following form:

$$
\ln(P_{kt}) = \begin{cases} 
    a - \eta \ln(Q_{nt}) - \gamma \ln(Q_{ot}) & \text{if } k = n \\
    a - \eta \ln(Q_{ot}) - \gamma \ln(Q_{nt}) & \text{if } k = o
\end{cases}
$$

All parameters in the system are greater than zero. Symmetric demand between $o$ and $n$ implies that the intercepts, inverse own-price elasticities, and inverse cross-price elasticities are equal across generations. Propositions will make explicit when the functional form of log-linearity is invoked to facilitate proof.

This model captures the salient features of the product life cycle of DRAM and many other computer components. Every several years, chip makers invest in costly new plants with fixed capacity. Firms enter each DRAM product generation with high cost, and reduce cost by learning as a function of cumulative output. Firms compete against rival firms’ products in the same generation and adjacent generations. They exploit a cost advantage over rivals if it develops, and eventually exhaust learning on a generation. This process repeats for every product generation.

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13This assumption is invoked in section 2.2 below to model collusive punishments within a Markov perfect equilibrium framework. Widespread knowledge of fabrication capacity levels as well as market research reports detailing quarterly firm-level shipments allow firms to monitor output. 14Product generations could also be considered vertically differentiated, i.e. assuming that demand for a new chip exceeds demand for an old chip at equal prices. Although this is generally true in DRAM, adjacent generations often contain identical underlying technology, so that price is the determining purchase factor. To the extent that new generations are more preferable than old ones, the demand substitution resulting from successful collusion on old generations will be even greater than the model predicts.

15Examples include microprocessors, static random access memory (SRAM), flash memory, hard disk drives (HDD’s), solid state drives (SSD’s), optical disk drives (ODD’s), servers, LCD panels, and graphics cards.

2.2 Equilibrium and Payoffs

Let the payoff of firm $i$ in period $t$ be $\Pi_{it}(q_t; s_t)$, where $q_t \in \mathbb{R}_{>0}^2$ is the vector of actions (quantities) across generations and firms, and $s_t$ is the vector of payoff-relevant state variables across generations and firms.

The equilibrium concept is considered to be Markov perfect: supergame strategies that constitute a Nash equilibrium, conditional on the state of the system, in every subgame of the original game.

Accordingly, the state space $s_t = (c_t, z_t)$ is comprised of a vector of marginal costs $c_t$ and a vector of indicator functions $z_t$ that denotes whether firms have deviated from a collusive strategy. $c_t$ is comprised of piecewise functions for generation- and period-specific marginal costs, as outlined above:

$$c_{ikt} = \begin{cases} \max\{c_1 \cdot f(q_{ikt-1}), \mathcal{C}\} & \text{if Phase } \leq 2 \\ \mathcal{C} & \text{if Phase } \geq 3 \end{cases}$$

The second payoff-relevant variable $z_t = (z_{ot}, z_{nt})'$ allows for the possibility of collusion through punishments based on the rival’s previous actions. Let $z_{kt} = (z_{ikt}, z_{jkt})$, $z_{ikt} \in \{0, 1\}$. If $i$ deviated from a collusive strategy on generation $k$ in any period $\{1, \ldots, t-1\}$, then $z_{ikt} = 1$. If $i$ did not deviate from a collusive strategy, or no collusive strategy was agreed upon, then $z_{ikt} = 0$. For simplicity, the model follows Fershtman and Pakes (2000) in considering only grim trigger punishments: if $z_{ikt} = 1$, then $z_{ikv} = 1$ for all $v > t$.

Firm $i$’s profit maximization function in noncooperative play is:

$$\max_{q_{ikt}} \Pi_{it} = \sum_{t=\tau}^{\infty} \sum_{k=0}^{n} \delta^{t-\tau} \left[ P(Q_{kt}; Q_{-kt}) q_{ikt} - C(q_{ikt}, q_{ikt-1}; c_l, \mathcal{C}) \right]$$

Firm $i$’s first order condition for a product at the first phase of its life cycle, i.e. product $n$ in period $\tau$, is:

$$\Rightarrow \frac{\partial \Pi_{i}}{\partial q_{in\tau}} = P_{n\tau} + \frac{\partial P_{n\tau}}{\partial q_{in\tau}} q_{in\tau} = \frac{\partial C_{in\tau}}{\partial q_{in\tau}} + \delta \frac{\partial C_{in\tau+1}}{\partial q_{in\tau}} \cdot q_{in\tau+1} - \frac{\partial P_{o\tau}}{\partial q_{in\tau}} q_{i0\tau}$$

$$= c_1 + \delta c_1 \frac{\partial f}{\partial q_{in\tau}} q_{in\tau+1} \text{ Learning } < 0$$

$$- \frac{\partial P_{o\tau}}{\partial q_{in\tau}} q_{i0\tau} \text{ Cannibalization } > 0$$

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17 Trigger and stick-and-carrot punishments of all types share the property that the extent of possible punishment depends on marginal costs and therefore on firms’ accrued learning. Equilibria are modeled more generally with testable implications in section 2.4.
The first-order condition illustrates the competing production incentives that firm $i$ faces during a product’s first phase. Learning-by-doing, which is based on the learning rate and discount factor, induces it to produce more than it would if cost were static. It is constrained from selling output as if cost were at its end-phase minimum $c$, however, by the presence of its own competing product.

2.3 Collusion Can be Differentially Successful

This section assesses the incentives of firms to enforce a collusive equilibrium in the presence of learning-by-doing and multiproduct competition. To do so, it restricts the set of supra-competitive equilibria to the one that maximizes the static discounted sum of joint profits (i.e., the most profitable equilibrium). It compares the minimum discount factor necessary to sustain collusion on $o$ with the corresponding minimum discount factor necessary to sustain collusion on $n$. It shows under plausible conditions that the minimum discount factor is higher in the case of sustaining collusion on $n$ than on $o$, i.e. collusion is differentially successful by generation. This result forms the intuition to examine the implications of differentially successful collusion under a range of equilibria, considered in Section 2.4.

Assume that the game is at period $\tau$, where $o$ is in the second phase of its product life cycle and $n$ is in its first. Consider the strategy $\sigma'_i$, in which each firm maximizes the discounted sum of joint profits at $\tau$ and punishes deviation on generation $k$ at $\tau$ with Cournot reversion on $k$ forever after. Firm $i$’s joint profit maximization function at period $\tau$ is:

$$\max_{Q_{kt}} \Pi_{it} = \sum_{t=\tau}^{\infty} \sum_{k=o}^{n} \delta^{t-\tau} [P(Q_{kt}; Q_{-kt}) Q_{kt} - C(Q_{kt}, q_{ikt-1}; c_1, c_2)]$$

(2)

Note that $i$’s cost reduction for generation $k$ is still based on its own previous-period output $q_{ikt-1}$, not total previous-period output $Q_{kt-1}$. Firms can collude in the product market but they cannot collude in

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18 To focus on the central relationship between learning and incentive compatibility, this model excludes intertemporal strategic effects of firm $i$’s output of $k$ in $\tau$ on firm $j$’s output of $k$ and $-k$ in $\{\tau + 1, \ldots\}$. To the extent that firms play as intertemporal strategic substitutes, incentives to deviate are even stronger than those represented in the model. Zulehner (2003) and Siebert (2010) find evidence consistent with this phenomenon in DRAM.

19 For expositional clarity, the text focuses on single-product collusive strategies. Appendix A generalizes the joint profit maximizing result to the multiproduct collusive scenario by following the logic of Bernheim and Whinston (1990). It shows that the collusive equilibrium is strictly more sustainable for generation $o$ under single-product punishment than either $o$ or $n$ under multiproduct punishment. Under multiproduct punishment, firms can collude on both products only if $o$’s incentive compatibility constraint allows sufficiently high “slack enforcement” power to redistribute to n’s constraint.
the learning process to share gains from output across the two firms. In contrast to noncooperative play, in cooperative play i includes j’s output decision in its own optimization problem. It therefore accounts for the pecuniary externality inherent to Cournot competition and restricts output relative to the noncooperative case.

The following remark establishes a necessary condition for \( \sigma'_i \) constituting a Markov perfect equilibrium.

Remark 1. Define \( * \) and \( ** \) as noncooperative and cooperative joint profit maximization actions of the normal form game, respectively. If \( \sigma'_i \) constitutes a Markov perfect equilibrium for product \( k \) at period \( \tau \), then:

\[
\sum_{t=\tau+1}^{\infty} \delta^{t-\tau} \left( \Pi_{iktt}^* (\cdot) - \Pi_{iktt}^*(\cdot) \right) \geq \left( \Pi_{iktt}^* (q_{iktt}^*, q_{jktt}^*, q_{jktt}^*; s_t) - \Pi_{iktt}^*(\cdot) \right)
\]

The collusive strategy \( \sigma'_i \) must satisfy the incentive compatibility constraint at period \( \tau \). This implies that the profits from remaining on the collusive path at \( \tau \) are greater than or equal to the profits from deviating at \( \tau \). In considering whether to deviate from the joint profit maximizing quantity on \( k \) at \( \tau \), assume that \( i \) (i) is colluding with \( j \) at the joint profit maximizing quantity on \( -k \); and (ii) considers its decision to collude with \( j \) on \( -k \) fixed in future periods.

The fundamental difference between collusion on \( n \), holding fixed the collusive path on \( o \), and collusion on \( o \), holding fixed the collusive path on \( n \), is the decreased punishment to deviating on \( n \). To see this, consider the incentive that \( i \) has to deviate from the optimal joint profit maximizing output at \( \tau \), \( q_{n\tau}^{**}(\cdot) \), to produce \( q_{in\tau} (q_{jnt\tau}, q_{o\tau}^*) \geq q_{n\tau}^{**}(\cdot) \). By comparing the first-order conditions, it follows that the difference in

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20Hatch and Mowery (1998) and Macher and Mowery (2003) model engineering processes in semiconductors and find that learning is shaped more by organizational management, data analysis and equipment technology than explicit knowledge held by individual engineers. Firms are limited in the learning they can successfully translate between plants; it is unlikely that they could increase diffusion between firms without costly effort, planning, team-oriented communication and problem solving. There is no evidence to suggest any attempt was made in the DRAM cartel. See section 3 for more details on the learning process.

21The first part of this assumption is inconsequential: some characterization of competition on \( -k \) is required. The second part is the direct result of the single-market punishment framework; see Appendix A for the multiproduct case.

22Because two firms simultaneously choose the outputs of two products in each period, a firm’s optimal quantities and prices are always functions of the remaining choices. This is treated in notation as (\( \cdot \) throughout the paper.
resulting optimal (competitive) outputs of \( n \) in period \( \tau + 1 \) between \( i \) and \( j \) are:

\[
q_{in\tau + 1}^* (\cdot) - q_{jn\tau + 1}^* (\cdot) = \frac{\partial C_{in}}{\partial P_{n\tau + 1}} - \frac{\partial C_{jn}}{\partial P_{n\tau + 1}} = c_1 \cdot \left[ f (q_{in\tau}^* (\cdot)) - f (q_{jn\tau}^{**} (\cdot)) \right] \cdot \frac{\partial q_{in\tau}}{\partial P_{n\tau}} > 0 \quad (4)
\]

Deviation from the (fixed) joint profit maximizing value at \( \tau \) increases \( i \)'s profits at \( \tau + 1 \) relative to playing a static symmetric Cournot game. This is because \( f (q_{in\tau}^* (\cdot)) < f (q_{jn\tau}^{**} (\cdot)) \): \( i \)'s costs are lower than \( j \)'s costs based on \( i \)'s increased learning in the first period. Consequently, \( i \) gains a strategic advantage over \( j \) (the magnitude of which depends on the shape of demand) that mitigates the punishment \( j \) can impose upon it. The same effect is absent in the scenario in which \( i \) considers deviating on generation \( o \) at \( \tau \), because learning on \( o \) is complete by \( \tau \). This logic leads to the following result.

**Proposition 1.** Define \( \hat{\delta}_{kt} \) as the minimum discount factor that satisfies \( \sigma_i' \)'s ICC at \( t \).

If demand is symmetric between generations, fixed across time, and log-linear, then \( \hat{\delta}_{ot} < \hat{\delta}_{nt} \).

\[
\begin{cases} 
\delta < \hat{\delta}_{ot} < \hat{\delta}_{nt} \Rightarrow \text{neither } o \text{ nor } n \text{ enforcable} \\
\hat{\delta}_{ot} \leq \delta < \hat{\delta}_{nt} \Rightarrow \text{only } o \text{ enforcable} \\
\hat{\delta}_{ot} < \hat{\delta}_{nt} \leq \delta \Rightarrow \text{both } o \text{ and } n \text{ enforcable}
\end{cases}
\]

**Proof.** See Appendix C.1.

Proposition 1 conveys the intuition that it is strictly more difficult to collude on a generation at the early phase of a product life cycle, the generation \( n \) scenario, than the later phase, the generation \( o \) scenario. Symmetry between generations and fixed demand across time guarantee that the baseline levels of demand and marginal revenue are equal in both scenarios. When demand is log-linear, elasticity is also equal at each point along the demand curve. Absent any learning effects, these sufficiency conditions render the IC constraint 3 equivalent in each scenario. The strategic advantage owed to increased learning, however, makes the left-hand side of the constraint in the \( n \) scenario smaller than the left-hand side of the constraint in the
scenario. The \( n \) constraint therefore requires a higher \( \delta \) to sustain this collusive equilibrium than does the \( o \) constraint.\(^{23}\)

The next portion of Proposition 1 depicts the relationship between the firm-invariant discount factor and the minimum discount factor necessary to enforce \( \sigma'_i \). Observed conduct at \( \tau \) depends on \( \delta \): if it is sufficiently high or sufficiently low, firms are equal in their conduct toward both generations. If \( \delta \) is in between the range of values, however, collusive strategy \( \sigma'_i \) is enforcable on \( o \) but not \( n \).\(^{24}\) Appendix A shows that a similar relationship holds in the multiproduct punishment case.

### 2.4 Implications of Differentially Successful Collusion

The model considered thus far argues that learning-by-doing and multiproduct competition can create conditions under which collusion is *successful* on an older product generation but simultaneously *unsuccessful* on a newer product generation. To do so, however, the model restricts firms to play either the competitive or the static joint profit maximizing strategy; it does not consider the full set of supra-competitive Markov perfect equilibria. Consequently, it cannot rule out the empirical possibility that collusion is *equally* successful or unsuccessful between generations.

This section models the strength of collusion at the product- and time-varying level to develop a testable prediction of the hypothesis that collusion is successful for the older generation and unsuccessful for the newer generation. If collusion operates as such, it shows that demand shifts away from the newer generation toward the older generation. The demand shift raises output of the newer generation relative to the equilibrium in which firms compete on both generations.

\(^{23}\)Iso-elasticity eliminates the possibility that the \( o \) scenario could create a lower punishment to deviating or a higher benefit to deviating for demand-specific reasons. For example, the same-period gain to deviating could be higher in the \( o \) scenario than in the \( n \) scenario. Because demand is symmetric and \( o \)'s cost is lower than \( n \)'s cost at \( \tau \), equilibrium competitive quantities are greater for \( n \) than for \( o \) at \( \tau \). If demand is more elastic at lower points on the demand curve, e.g. with linear demand, then deviation would be more profitable in \( \tau \) in the \( o \) scenario than in the \( n \) scenario.

\(^{24}\)Intuitively, this result holds whenever firms play as strategic substitutes within a generation and output deviation in one period confers a strategic advantage in the next period. If some element of learning were to exogenously “spill over” to other firms within a generation, for example, both conditions are met if learning does not reduce rivals’ costs more than a firm’s own costs.
Reconsider firm \( i \)'s profit function and first order condition at period \( \tau \):

\[
P_{k\tau} + \frac{\partial P_{k\tau}}{\partial q_{ik\tau}}q_{ik\tau} + \frac{\partial P_{-k\tau}}{\partial q_{ik\tau}}q_{ik\tau} = \frac{\partial C_{ik\tau}}{\partial q_{ik\tau}} + \delta \cdot \frac{\partial C_{ik\tau+1}}{\partial q_{ik\tau}}
\]  

(5)

\[
P_{k\tau} + \theta_{k\tau} \left[ Q_{k\tau} \left( \frac{\partial P_{k\tau}}{\partial Q_{k\tau}} + \frac{\partial P_{-k\tau}}{\partial Q_{k\tau}} \frac{q_{ik\tau}}{q_{ik\tau}} \right) \right] = \quad "
\]  

(6)

\[
\theta_{k\tau} = \left( 1 + \frac{\partial q_{jk\tau}}{\partial q_{ik\tau}} \right) \frac{q_{ik\tau}}{Q_{k\tau}}
\]  

(7)

In this framework, \( \theta_{k\tau} \in [0, 1] \) is the conduct parameter that aggregates the average strength of collusion between firms \( i \) and \( j \) for generation \( k \) in period \( \tau \). As 7 shows, \( \theta_{k\tau} \) is based on the conjecture that \( i \) holds about \( j \)'s response to a change in \( i \)'s output in period \( t \). Marginal cost is composed of the static effect and the dynamic (learning) effect as before.

Bresnahan (1989) demonstrates that the conduct parameter has a clear interpretation for several specific supply types. In Cournot equilibrium, firms in competition hold their rival’s output fixed, so \( \frac{\partial q_{ik\tau}}{\partial q_{ik\tau}} = 0 \Rightarrow \theta_{kt} = \frac{1}{2} \). In the joint profit maximizing equilibrium, where firms collude perfectly, an output increase by \( i \) is met with an equal output increase by \( j \). In that scenario, \( \frac{\partial q_{jk\tau}}{\partial q_{ik\tau}} = \frac{q_{ik\tau}}{q_{ik\tau}} \Rightarrow \theta_{kt} = 1 \). In other supra-competitive equilibria, it takes values between \( \frac{1}{2} \) and 1 corresponding to other permutations of single- or multi-product punishment strategies.\(^{25}\)

Define the set of conduct parameters \( \Theta = \{ \theta_t : \theta_t \in [0, 1] \times [0, 1] \} \). There is a (singleton) subset of \( \Theta \) in which firms cannot sustain any collusive equilibria and therefore play the Cournot equilibrium. Call this subset \( \Theta^* \subset \Theta = \{ \theta_t : \theta_{ot} = \frac{1}{2}, \theta_{nt} = \frac{1}{2} \} \). Similarly, call the subset of conduct parameters in which firms possess the minimum discount factor necessary to sustain a collusive equilibrium for \( o \), but fail to reach any collusive equilibrium for \( n \), \( \Theta^{**} \subset \Theta = \{ \theta_t : \theta_{ot} > \frac{1}{2}, \theta_{nt} = \frac{1}{2} \} \). The following result establishes a testable prediction of the hypothesis that firms’ conduct is drawn from the set \( \Theta^{**} \) rather than the set \( \Theta^* \).

\(^{25}\)Corts (1999) shows that the empirical estimation of \( \theta \) depends upon untestable functional form assumptions on the curvature of demand. I consider only \( \theta \)'s value in theory and do not empirically test for it.
Proposition 2. Let \( \Psi_{kt}(\Theta) \) be the correspondence from \( \Theta \) to the set of optimal solutions for firm \( i \) on generation \( k \) at time \( t \): 
\[
\Psi_{kt} = \{ q_{ikt} : q_{ikt} \in \text{argmax}_{q} \pi_{it}(q_{it}; s_{t}; \Theta) \}.
\]
If demand is such that generations are strategic substitutes, then 
\[
q_{in\tau}^{*} \in \Psi_{n\tau}(\Theta^{*}) < q_{in\tau}^{*} \in \Psi_{n\tau}(\Theta^{**}) \forall q_{in\tau}^{*}.
\]

Proof. See Appendix C.3.

With empirical data sufficient to identify collusive and non-collusive time periods, Result 2 constitutes a testable prediction to bring directly to the data. It examines the consequences of equilibrium output for generation \( n \) at \( \tau \) if collusion is *successful* on generation \( o \) but *unsuccessful* on generation \( n \). \( q_{in\tau}^{*} \in \Psi_{n\tau}(\Theta^{*}) \) denotes \( i \)'s output of \( n \) in the baseline Cournot-Nash equilibrium, when firms compete uniformly on both generations. \( q_{in\tau}^{*} \in \Psi_{n\tau}(\Theta^{**}) \) is \( i \)'s output of \( n \) in any equilibrium in which firms collude upon \( o \) to some degree, but do not collude on \( n \) to any degree. The necessary condition states that industry output for \( n \) is greater in the latter equilibrium, when firms are able to collude on \( o \) to some degree, than in the former equilibrium, when there is uniform competition.

The intuition of the result is as follows. When firms reach a collusive equilibrium on \( o \), they internalize the pecuniary externality of Cournot competition. Therefore firms cut the output of \( o \) relative to the Cournot-Nash benchmark. In response, as long as firms consider \( o \) and \( n \) to be strategic substitutes, the demand for generation \( n \) shifts outward. Therefore firms unambiguously increase the output of \( n \) relative to the Cournot-Nash benchmark. Figure 2 depicts the result graphically with linear demand, when intergenerational strategic substitution holds by default; appendix C.3 also generates the sufficient condition with log-linear demand.

![Figure 2 about here.]

In addition, it is important to point out that the possibility of increased output of the new generation at \( \tau \) carries significant further dynamic effects. Because of learning-by-doing, \( c_{in\tau+1} = c_{1} \cdot f(q_{in\tau}) < c_{in\tau} \): future costs decline as a function of current output. When current output increases, firms learn a greater amount than they otherwise would, which reduces cost in the future. Reduced cost imposes downward pressure on

\[\text{(If collusion is "more successful" on } o \text{ than on } n, \text{ i.e. } \frac{1}{2} < \theta_{n\tau} < \theta_{o\tau}, \text{ the same intuition applies, but the result requires an additional sufficient condition. Firms face competing output incentives on } n: \text{ collusion induces them to restrict output, but the net demand shift is still away from } o \text{ and toward } n. \text{ If the cross-price elasticity of demand } \frac{\partial P_{n}}{\partial Q_{o}} < 0 \text{ is sufficiently great, the output expansion effect dominates the output restriction effect.)}\]
prices, although it is ambiguous on net whether the price of the newer generation increases or decreases relative to uniform competition. Lower prices of the newer generation relative to uniform competition are consistent with increased accrued learning through the demand shift described here, and they will also be tested for in the empirical analysis to follow.

3 DRAM Industry and Market

Semiconductors are crystals—usually silicon—that serve the essential role of connecting the electronic circuits that make up a microchip. Microchips are a bedrock of the electronics revolution and provide the processing, memory, speed, and performance ability of computers and many electronic devices. A critical feature of the microchip is its capacity: the number of transistors per square inch. Increases in capacity reduce the effective cost of a microchip, or, equivalently, increase its speed. Capacity has risen sharply since the industry’s inception in the 1970s, famously corresponding to “Moore’s Law”: the maximum capacity of an individual chip doubles every 18-24 months.

DRAM is a type of memory chip that complements a microprocessor by refreshing the transistor repeatedly. The total capacity of DRAM chips in a module represents its bit density (“density”), and DRAM product generations are measured by density. Like most microchips, it is within generations that intensive learning-by-doing takes place.\textsuperscript{27} DRAM products are largely homogeneous goods within a density generation, and are substitutable between density generations based on the customer’s preferences for memory speed.\textsuperscript{28} Several different density generations are available at any time, and because of the sequential nature of releases, they are always sequentially ordered between different points in their life cycles.

The only way to increase capacity is through the photolithography process.\textsuperscript{29} For each duplication in capacity, the new lithographic process initially produces a yield of zero chips because of hundreds of nanoscale level-steps requiring precise light, air, and dust conditions. Engineers continuously fine tune chemical conditions, employ alternative techniques, phase in higher-technology equipment, and analyze the resulting data.

\textsuperscript{27}See Gruber (1998) for evidence of intergenerational learning in EPROM memory chips.
\textsuperscript{28}Noll (2014).
\textsuperscript{29}The other way to reduce cost per chip is to increase the size of the wafer itself, which allows more chips per lithographic batch. Such changes occurred about half as frequently as capacity advancements during the 1980s and 1990s; see Kang (2010) Table 3-2, citing Brown & Linden (2009).
in a trial-by-error process. Hatch and Mowery (1998) find that the most important adjustments engineers make to increase yield are in *parametric processing*, determining the minute range of chemicals to be applied at each step, followed by adjustments in air particle contamination. Problem diagnoses in these two areas gradually increase numbers of usable chips, and increasing yield drives the cost of each chip down as a function of output.

In addition to the capacity level, DRAM innovation also occurs along the *technology* level. Unlike the capacity innovation process, technology standards are jointly developed by industry participants. In the early 2000s, two different types of new technologies were competing to become the next industry standard. Double Data Rate Synchronous DRAM (“DDR”), preferred by the industry SSO, competed with Rambus DRAM (“RDRAM”), designed and patented by the Silicon Valley firm of the same name. Appendix B discusses competition between these technologies and shows that neither technology began to proliferate until after the cartel period, which precludes the possibility of competition over technologies confounding any of the empirical cartel results to follow.

For the data period under study, PC’s were the dominant application of DRAM.30 They were the only significant end use throughout the 1980s and early 1990s (Flamm and Reiss, 1993); they comprised about 90% of the market in the late 1990s and early 2000s (Third Amended Class Action Complaint, MDL No. 1486, pg 76); and 80% of the market in 2006 (Kang, 2010).31

Because of the large capital outlays for new fabrication plants and variability in demand growth for computers, the DRAM industry has been highly cyclical since its inception.32 In the late 1990s, the industry faced significant overcapacity despite steady PC growth.33 After several firms exited the market amid falling prices and steep losses, in 1998 the largest firms formed a cartel to cut production, raise prices and restore profitability.34

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30 Memory manufacturers contract with original equipment manufacturers (OEM’s) on a biweekly or monthly basis.

31 In recent years, the market for DRAM has begun to shift from traditional PC’s toward mobile smart phones and computer tablets, which use lower-power memory but sell many times the units as PC’s. See “Why Growth in Mobile Devices Will Fuel Micron’s DRAM Shipments,” Forbes, 1/15/2013 http://www.forbes.com/sites/greatspeculations/2013/01/15/why-growth-in-mobile-devices-will-fuel-microns-dram-shipments/.

32 Capital depreciation accounted for about 50% of marginal cost in the 1990s and 80% in the 2000s. Source: see Footnote 16.

33 “But too many new plants were built several years ago in a rush to benefit from a boom many thought would never end...The glut led to a free fall in prices. In-Stat expects a 21 percent decline in revenue this year, to $15.6 billion.”—Dallas Morning News, June 1998 http://articles.chicagotribune.com/1998-06-29/business/9807100053_1_memory-in-personal-computers-dram-memory-chip-business.

Figure 3 details the events surrounding the cartel period. After intermittent communication in 1997, the cartel operated from the second quarter of 1998 through the first quarter of 2001. Noll (2014) relates that it disbanded when South Korean firm Hynix applied for bankruptcy protection, and restarted after state-controlled banks bailed out the company for $6-7 billion.\footnote{“DRAM Rivals Question Korean Government’s Role in Hynix Bailout,” EE Times, 11/5/2001 http://www.eetimes.com/document.asp?doc_id=1131477.} The cartel ended with DOJ subpoenas in June 2002 following a public accusation of collusive behavior by the CEO of Dell Inc., Michael Dell. The empirical results to follow take only the 12 continuous quarters of cartelization between 1998 and 2001 to mean the “cartel period,” except where noted otherwise. Results are materially identical upon adding the first two quarters of 2002 to the definition.

4 Data

I use a proprietary dataset from industry-leading market research firm Gartner Research that lists quarterly shipments by firm and density generation, and quarterly market price by density generation, for all firms in the DRAM market from 1974-2011. I narrow the data to the period for which downstream demand data is reliably available: 1988-2011. DRAM demand is proxied by a time series of worldwide quarterly PC shipments obtained from Gartner research reports. This data is available annually from 1988-1996 and quarterly from 1997-2011.

All prices are given in US dollars and subsequently deflated to year 2000 values by the Consumer Price Index (CPI). Additionally, the Gartner data includes output per firm by DRAM technology after 2001. Firm names allow accurate tracking of mergers, entry, and exit throughout the data sample.

In the empirical work to follow, I make use of two subtly different measures of the market price. The first (employed in previous literature) is the price per module of DRAM generation \(k\) sold at time \(t\). Because DRAM chips are sold as modules, it is the actual price that buyers pay for a given DRAM generation. Another way to represent DRAM price is through the price of an individual chip standardized by its capacity. The DRAM price per \(MB\) is the market-wide price of a chip divided by its number of megabytes (MB’s).
Figure 4 plots the price per module by generation for all 11 generations of DRAM from 1988-2011. The pattern is clear: price is high in initial periods, and it declines in a logarithmic shape as a generation ages. The most significant price changes occur within the first five to ten years of a generation. This is consistent with classic models of learning-by-doing.

Figure 5 shows the price per MB averaged and weighted by sales across generations, from 1988-2011. The standardized price declined through the sample because a fixed DRAM chip becomes cheaper as density increases. However, there were multiyear cycles of sharp price decreases interspersed with price plateaus or slight increases. The shaded area represents periods of cartel activity. The figure shows that price vacillated during the cartel period, staying roughly constant from 1998-2000 before dropping in 2001. The drop coincides with the period at which the dot-com bubble burst and the cartel disbanded. Price increased in the first two quarters of 2002, when the cartel regrouped, before declining again after mid-2002 as the DOJ initiated its investigation.

Figure 6 plots the change in aggregate DRAM price per MB against the change in worldwide PC shipments. It shows that most of the variation in DRAM price can be explained by variation in PC shipments. The effects of the 2001 dot-com bubble crash are particularly striking: both series reach their troughs in concert. Regression specifications make use of the change in PC shipment rates in explaining generation-level DRAM price throughout the product life cycle.

Forty-eight different firms appear in the dataset, with a maximum of 24 active firms in 1996. As many as seven different product generations were active at any given cross-sectional point in the dataset, although two to three accounted for most of the sales. Eleven different product generations, from 256Kb to 2Gb, appear with sufficient frequency to include in the analysis. Table D2 lists each DRAM generation

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36 See Siebert and Zulehner (2013) for an empirical analysis of firm entry and shakeout in the DRAM industry.
37 Figure E1 depicts the evolution in market shares between five DRAM generations active during the cartel period.
38 I also discard two minor “mini-generations,” 2Mb and 8Mb, that briefly appear between industry standard generations in the 1990s.
and its years active within the sample period. At the market level, the industry is a classic oligopoly: ten firms accounted for 85% of output across generations in 2000. The four largest firms—Samsung, Infineon, Micron, and Hynix—held 63% of the market. Table D3 charts $C_4$ concentration ratios by generation from 1994-2004.

5 Empirical Results

The theoretical model presented above generates testable predictions for the effect of collusion on market prices and outcomes. It is based on the intuition that collusive equilibria are more difficult to sustain on new generations than they are on old generations. The larger is the disparity in average strength of collusion between generations, the larger is the demand shift toward newer generations. This leads to a sufficient condition that is testable: older generations sell less output in the cartel period than they would in non-cartel periods, and newer cartel generations sell more output in the cartel period than they would in non-cartel periods. It also implies that the change in price attributable to the cartel is higher for older generations than newer generations, and ambiguous in sign for newer generations.

In this section, I estimate two types of empirical relationships pursuant to these predictions: (1) the effect of the cartel on the dependent variable, output or price; (2) the effect of the cartel on the dependent variable with respect to product cycle age. The first relationship is identified by repeated product life cycles among generations before, during, and after the cartel. I compare observations a given amount of quarters from generation or firm entry within the cartel period to other observations the same amount of quarters from generation or firm entry outside the cartel period, conditional on a proxy for market demand.

The second relationship is the differential effect of collusion with respect to generation age. Its identification arises from two sources. First, because the cartel was active for 12 quarters, each active generation provides time-series variation in age. Second, five different generations were at sequentially ordered stages of their product cycle at each point in time during the cartel. This provides cross-sectional variation between generations. The latter source is especially strong in ruling out the possibility that changes in firms’ dis-

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39I pool the sales of LG Semiconductor with Hynix, which purchased the company in 1999.
count factors over time—through macroeconomic conditions, firm-specific financial health or management changes—bias the results.

5.1 Cartel Output Effects

Figure 7 plots logged generation-level output of DRAM for the first 12 quarters of each generation. It displays data from the 11 even generations under study, with each dot representing one quarter of output. Output generally increases from quarter to quarter during the early stage of production, as existing firms increase their output and new firms enter.

Firms started selling units of 128Mb and 256Mb chips during the cartel period, which is shaded. 128Mb was the newest generation from 1998 until 1999, when firms began producing 256Mb chips. These two generations were therefore in the early stage of their product cycles during the cartel period. Sales of the 128Mb and 256Mb generations immediately stand out: initial output values are orders of magnitude greater than the corresponding values during non-cartel periods before and after the conspiracy.\(^{40}\) It is especially noteworthy that 128Mb and 256Mb output is greater than post-cartel generations, because the increasing market for DRAM over time implies gradually increasing overall output.\(^{41}\)

To further investigate the hypothesis that cartel output increased for the newer generations, I estimate the following regression:

\[
\begin{align*}
\log(q_{ikt}) &= \beta_1 \text{FirmAge}_{ikt} + \beta_2 \text{FirmAge}^2_{ikt} + \beta_3 \text{GenAge}_{kt} + \beta_4 \text{GenAge}^2_{kt} + \beta_5 TT \\
&\quad + \beta_6 Y_t + \beta_7 Y_t \times \text{GenAge}_{kt} + \beta_8 Y_t \times \text{GenAge}^2_{kt} + \beta_9 I(\text{Cartel})_{kt} + \epsilon_{ikt}
\end{align*}
\]

This specification regresses the log of a cartel-participating firm’s output for generation \(k\) at time \(t\) on measures of firm age, generation age, time trend, demand, and an indicator variable for the cartel period. \(\text{FirmAge}_{ikt}\) and its square denote the elapsed quarters since firm \(i\) began production in generation \(k\).

\(^{40}\)They are also far greater than initial output values for the three pre-1982 generations: 4Kb, 16Kb and 64Kb.

\(^{41}\)Figure E3 shows that peak-stage output indeed increases greatly between generations over time.
GenAge\(_{kt}\) and its square represent the elapsed quarters since the first firm in generation \(k\) began output. These variables account for the positive trend in output during the early phase of a product cycle, when cost decreases and firms pursue learning gains, to the negative trend later in the product life cycle, when output crosses its peak and firms shift production to a newer generation. TT is a time trend included to capture the increase in shipments over time depicted in fig. E3. \(1(Cartel)_{kt}\) is an indicator variable equal to one during the cartel time period for each generation \(k\) and zero otherwise. This variable permits separate estimation of the effect of cartelization on output by generation.

\(Y_t\) is a demand shifter representing the growth rate of worldwide PC shipments. Departures from the baseline rate of PC growth, which is mostly positive through the sample period, are taken as exogeneous changes in the demand for DRAM.\(^{42}\) Interactions between \(Y_t\) and GenAge\(_{jt}\) allow the effect of a change in PC shipments to be stronger in the initial phase of a product cycle, when OEM’s may increase production of memory-intensive computers, than later stages.

Regression 9 is a reduced form equation that imposes demand- and supply-side conditions to identify the effect of the cartel on firm output. On the demand side, it assumes that PC shipment growth affects \(k\) and \(-k\)’s output equally at equal generation age. Although this condition is untestable, fig. 6 shows that the overall DRAM price is highly correlated with the PC shipment rate throughout the sample period, even without conditioning on generation age. The estimation adds interactions of PC growth with generation age to more flexibly estimate this relationship.

Regression 9 also assumes that supply-side factors vary as a function of firm age and generation age. Consider two firms \(i\) and \(j\) that produce chips from two different generations \(k\) and \(-k\) at two different points in time. If \(k\) and \(-k\) sold chips for the same number of quarters, and if \(i\) and \(j\) sold chips within \(k\) and \(-k\) for the same number of quarters, then the regression assumes that \(i\) and \(j\) will see produce the same amount in the next quarter, conditional on the increasing time trend and the demand proxy. This corresponds to the structure of the theoretical model: a firm’s learning rate depends on its phase in the product life cycle. The model’s hypothesis is that output will be most sensitive to time in the initial quarters.

\(^{42}\) The proliferation of PC’s from the 1980s through the 2000s was due to the decreasing overall cost of the computer’s components, of which DRAM comprises only 5-10%. There is no evidence that DRAM prices themselves drive a significant portion of PC sales. Figure 6 depicts the correlation between \(Y_t\) and the aggregate price of DRAM.
following firm or generation entry, and decline thereafter. Violations of this condition are considered in subsequently.

Table 1 shows that the strong industry-level effect observed in Figure 7 carries over to the firm level for cartel participants as well. It displays the results of regression 8 with and without controls for demand. Coefficients for firm age, generation age, and time trend take the expected signs, with primary terms positive and squared terms negative signaling the pre- and post-peak phases of the product life cycle. The demand proxies in the right hand side panel also take the expected signs, with the PC Growth Rate positively associated with output levels at the earliest stages of the product cycle.

The cartel indicator variables are strongly positive and consistent for the 64Mb, 128Mb and 256Mb generations in both specifications, with coefficient estimates indicating an output increase of several times the competitive value. In contrast, the coefficient is negative for the 16Mb generation, and negatively significant \((100 \times (e^{-0.74} - 1) = -52.2\%)\) in the 4Mb generation. Wald tests for equality reject the joint hypotheses that either of the latter two coefficients arise from the same distribution as either of the former three coefficients. These results provide strong evidence that the cartel’s effect was twofold: participants restricted output on older generations and raised output on newer generations.

The coefficients in Table 1 are consistent under the demand- and supply-side identification conditions discussed above. The primary threat to identification is unobserved production capacity levels. As section 3 explains, lumpy plant investment is well understood to lead to capacity excesses and shortages over time. Moreover, the historical record indicates that capacity levels of DRAM manufacturers rise and fall cyclically at the industry-level.\(^{43}\)

The results in Table 1 are robust to including an industry-wide capacity variable that captures these cycles. I follow Gardete (Forthcoming) in exploiting Moore’s Law to implicitly identify periods of industry-wide over- or under-capacity.\(^{44}\) Figure 8 plots the logged aggregate DRAM price per MB against the logged

\(^{43}\)Memory analyst Jim Handy: “During the profitable years...they invest. But they all have their good years at the same time and they all invest in new factories at the same time. Two years later, the factories are all up to speed and you have a glut...In about two more years, demand usually catches up to the capacity they added four years earlier.” Source: see Footnote 16.

\(^{44}\)Exploiting Moore’s Law appears to be the most effective approach to capture unobserved capacity levels without possessing private data from manufacturers. Specifically, the approach performs better than an alternative based on realized capacity utilization ratios from the Federal Reserve Board of Governors. That series, constructed only from reported capacity levels of
Moore’s Law price index, which begins at the same initial value and halves every 24 months. DRAM price trend tracks Moore’s Law price trend closely: it is centered around the predicted values over the duration of the sample period, but drops faster or slower than predicted values within various sub-periods.

I hypothesize that these sub-periods correspond to the known, industry-wide capacity cycles and define a continuous variable to index them. For example, leading up to the cartel period in the mid-1990s, the figure shows that DRAM price dropped lower than its predicted values. This period coincides with a capacity glut centered around technology transition in the mid-1990s, as discussed in section 3.

The variable “Average Rate of Change of Difference” in fig. 7 is constructed to capture such events. It is defined as the rate of change of the Moore’s Law value, minus the DRAM value, averaged over the three most recent quarters, and multiplied by ten to facilitate inspection in the graph. The implied capacity level varies in a cyclical manner, as expected. Between the start and end of the cartel, when prices are hypothesized to be determined non-competitively, I fix the measure at its pre-cartel value of 2 log points.45 If demand is fully identified and there are no other supply-side factors that do not vary at the firm age- or generation age-levels, then the implied capacity level is hypothesized to capture industry-wide unobserved capacity.

Table 2 displays the results of various specifications that include the implied capacity level, as well its interactions with firm age and generation age. Specification (1) omits the collusive period to show that the baseline values of the measure of implied capacity is positively and significantly correlated with firm-level output, conditional on supply-side variation. Specification (2) extends the time frame to include the collusive period, and (3) adds demand proxies. Specification (4) adds interactions of implied capacity with firm age and generation age, which also take the hypothesized signs with significance. Across specifications, the cartel dummy coefficients display the same trend as above. Although the 16Mb and 256Mb generations drop to U.S. firms, contains industry categorizations for “Semiconductors and related equipment” (G33441), “Computer and peripheral equipment” (G3341), and “Computers, communications eq., and semiconductors” (HITEK). Specifications using any of these measures instead of the chosen measure are available upon request.

Of course, firms may have colluded tacitly in non-cartel periods. To the extent that successful collusion restricted output, it biases the cartel coefficients upward. But it cannot explain positively estimated cartel coefficients, nor can it explain the disparity in estimated cartel coefficients between generations.
insignificance in the fully specified regressions, the strong estimate of decreased output for the older 4Mb generation and increased output for the newer 64Mb and 128Mb generations remains.

5.2 Cartel Price Effects

I now describe and estimate the effect of the DRAM cartel on the price of each active generation. Figure 9 uses DRAM prices per MB to represent all five cartel generations at the same time on the same axis. The shaded area depicts the cartel period. By inspection, the price of the older, outgoing 4Mb and 16Mb chips steadily rise, while 64Mb price rises and falls jaggedly to stay roughly equal on average. The prices of the newer two chips continue to fall.

Figure 10 restricts the price series to the 128Mb and 256Mb generations, which entered during the first period of collusion and accounted for the majority of market share by the second period. It extends the x-axis to show the price trend within these generations over the first and second cartel periods. Prices decline in the first phase, but rise sharply in the second phase, before the cartel is disbanded. The visual evidence in figures 9 and 10 is consistent with the results of the model: firms are more likely to reach collusive equilibria as the product cycle progresses.

I test this intuition more formally by conditioning on the product cycle phase in the following regression.

\[
\ln(P_{jt}) = \alpha + \beta_1 \text{LogGenAge}_{jt} + \beta_2 Y_t + \beta_3 Y_t \times \text{GenAge}_{jt} + \beta_4 Y_t \times \text{GenAge}^2_{jt} + \beta_5 \mathbb{1}(\text{Cartel}) + \epsilon_{jt}
\]  

(9)

This regression differs from 8 in two significant ways. First, the dependent variable \(\ln(P_{jt})\) is the logged industry-level price of generation \(k\) at time \(t\). Second, the regression is run separately for each of the five cartel generations. The sample for each regression is restricted to a total of 24 quarters before, during, and after the quarters of cartel activity for the cartel generation in question. This procedure is conducted to
maximize the statistical power of the test because all variation is at the generation-quarter level. \(1(Cartel)\) therefore estimates the average effect of the cartel on the price of \(k\), based on the stage of the product life cycle. It is not equivalent to an “overcharge,” because the regression conditions on the stage of the life cycle rather than on cost determinants.

Table 3 and Table 4 show the results from regression 9 with and without interactions of DRAM demand over the product cycle. Generation age enters negatively and significantly in all specifications, consistent with a decreasing effect of the product cycle phase on price. The coefficients for \(Y_t\) and its interactions indicate that the effect of PC growth on DRAM price is positive and significant, that it increases in magnitude in the ramp-up phase of a product cycle, and that its effect attenuates as a cycle passes its peak.

The \(1(Cartel)\) variable estimates the average effect of the cartel on price for generation \(k\). Comparing estimates between generations, the results are consistent with the model’s predictions as well as output regressions from Table 1. Point estimates of the average price effect are greater for the two oldest generations, 4Mb and 16Mb, than the three most recent generations, 64Mb, 128Mb, and 256Mb. The bottom three rows display the p-value from a joint test of equality of the cartel coefficient between generations. Whereas the estimated price increase for the 16Mb generation is \(100 \times (e^{0.196} - 1) = 21.7\%\) at the 10% confidence level, it is significantly different from that coefficient at the 5% confidence level for each of the 64Mb, 128Mb, and 256Mb generations. This suggests that the cartel colluded successfully in the 16Mb generation, but unsuccessfully in the more recent generations.\(^{46}\) Table D1 shows that this finding is robust to including the implied capacity variable calculated through Moore’s Law, which does not explain a significant degree of price variation.

Due to the relatively small number of generation-quarter level price observations, cartel price estimates for a particular generation should be treated more cautiously than equality tests of the price estimates between generation-quarters.\(^{46}\) Figure E2 shows that whereas the share of generation market share that cartel members comprised was relatively constant and at least 80\% for the 16Mb through 256Mb generations, it was only 50\% and declining for the 4Mb generation. Insider market share declined as the largest firms exited the generation and smaller fringe firms entered, which could explain a small price effect for 4Mb despite the sharp output restriction among insiders estimated in Table 1 and Table 2.
generations. However, it is noteworthy that point estimates for the 64Mb, 128Mb, and 256Mb generations are negative, though only the 128Mb generation reaches statistical significance. The 128Mb price during the cartel is estimated to be $100 \times (e^{-0.70} - 1) = -68.2\%$ lower than without the cartel. These findings lend further credence to table 1’s result that newer generations produced more during the cartel than they would have in competition. Moreover, they imply that increased output increased the rate of learning among newer generations, which decreased the cost of producing newer generations relative to the same stage of the product life cycle in the absence of the cartel.

Regressions of average price level do not capture any time trend in price during the cartel period. If the rate of the cartel price change increases as a function of product age, as the model predicts it does, then the average price level understates the actual price level at each quarter. To account for these possibilities, I add a cartel indicator-age interaction term to regression 9 and display the results below.

Table 5 displays estimated coefficients from the regression with an average and a per-quarter cartel price effect, pooling each variable across generations. The first column includes all five cartel generations. Because of the magnitude of the negative price effect on the 128Mb generation, it may also be instructive to exclude it from the regression, as the second column does. Results from both specifications are consistent with the model’s predictions: the interacted coefficient of cartelization and generation age is strongly positive and significant. This indicates that the effect of the cartel on prices increases as a function of generation age. Without adding up coefficients from the regression, however, it is not evident how the estimated cartel price compares to the counterfactual non-cartel price in each period.

Figure 11 plots predicted price coefficients from the model with and without the cartel indicator variable, including standard errors. The x-axis is generation age and the y-axis is logged price per module. The figure estimates the expected price path of a generation from its first period through the rest of its product cycle. It is consistent with successful collusion later in the product life cycle and increased learning early in the product life cycle. Specifically, increased learning pushes the price below its competitive counterpart for the first 20-24
quarters, whereas output restriction raises the price in the following quarters. The break-even point occurs roughly at a generation’s peak in its sixth year. It is important to note that the estimates underlying this figure include multiproduct competition with other generations. Without multiple generations, the effect in the second half of the product life cycle would be expected to persist, but the learning gains in the first half of the life cycle would not.

6 Conclusion

If firms in learning-by-doing industries successfully refrain from competition, the cost to society could be especially large, because firms would also reduce the rate at which they lower long-term costs. The fundamental insight of this paper is that the effectiveness of collusion in such markets is determined by the rate of learning. The effectiveness of collusion in one product generation impacts equilibrium price and output of competing product generations. In particular, successful collusion in a mature generation shifts demand toward newer product generations. If firms are unsuccessful in colluding on newer product generations, the demand shift induces them to raise output. Increased output results in newer generations learning more than they would have in a uniformly competitive counterfactual.

Empirical analysis of the DRAM cartel shows evidence consistent with the model. Firms are estimated to produce up to 50% less output for the 4Mb and 16Mb generations during cartelization than competition. On the other hand, firms produced substantially more output for the frontier 64Mb, 128Mb, and 256Mb generations during cartelization than competition. Moreover, the cartel price estimates of the former generations are significantly greater than those of the latter generations, which are negative. The results imply that firms colluded successfully on the 4Mb or 16Mb generations, which shifted demand toward the 64Mb, 128Mb, and 256Mb generations. They imply further that firms learned more during 12 quarters of cartelization than they would have during 12 quarters of uniform competition.

This paper carries implications for antitrust and industrial policy, particularly as it relates to many high-technology industries that experience large cost reductions through learning. As technology becomes increasingly expensive to downsize at the nanoscale level, it is well understood that semiconductors of
all types are reaching a limit to cost reduction. This means that overall learning rates are slowing down while other structural features that facilitate coordination—product homogeneity, multimarket contact, R&D cooperation—remain in place. Competition authorities should be aware that the conditions favoring shakeout may also raise the likelihood of firms reaching collusive equilibria.

In addition, the DRAM case suggests that high-technology cartels can shift demand away from older generations and toward newer ones. Many of the largest electronics manufacturers in the world have settled charges of price fixing in related markets, including LCD panels and hard disk drives. There is anecdotal evidence that LCD manufacturers, spurred by increased incentives to roll out newer generations, increased the pace of these introductions during cartelization. Further research of these cases should be conducted to reveal the extent of substitution across product generations.

Finally, economists have long recognized that firms in learning industries may under- or over-invest in output depending on the learning rate, strategic entry deterrence, or predatory pricing. By showing evidence that the DRAM cartel induced increased learning among frontier generations, the present study suggests the possibility that subsidies or other credits designed to raise early-stage output could increase welfare. To generate a fuller picture of such possibilities, a more complete welfare analysis of the cost—and benefit—resulting from DRAM and other high-technology cartels may be illustrative.

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47 Mark Bohr, senior fellow and director at Intel, relates: “Everybody in our industry will acknowledge it is getting tougher with every new generation, [but] we are going to carry the Moore’s Law banner as far as we can.”—“Intel Details 14-Nanometer Chip Aimed at Tablets,” Wall Street Journal 8/11/2014. [http://online.wsj.com/articles/intel-details-new-chip-aimed-at-tablets-1407775008](http://online.wsj.com/articles/intel-details-new-chip-aimed-at-tablets-1407775008)
References


Table 1: Log Output of Cartel Firms on Covariates, 1988-2011

<table>
<thead>
<tr>
<th></th>
<th>(1) Coefficient (Std. Err.)</th>
<th>(2) Coefficient (Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm Age</td>
<td>0.175*** (0.014)</td>
<td>0.178*** (0.013)</td>
</tr>
<tr>
<td>Firm Age$^2$</td>
<td>-0.003*** (0.000)</td>
<td>-0.003*** (0.000)</td>
</tr>
<tr>
<td>Gen Age</td>
<td>0.338*** (0.012)</td>
<td>0.324*** (0.013)</td>
</tr>
<tr>
<td>Gen Age$^2$</td>
<td>-0.005*** (0.000)</td>
<td>-0.005*** (0.000)</td>
</tr>
<tr>
<td>Time Trend</td>
<td>0.041*** (0.001)</td>
<td>0.037*** (0.001)</td>
</tr>
<tr>
<td>PC Growth Rate</td>
<td></td>
<td>0.126*** (0.010)</td>
</tr>
<tr>
<td>PC Growth Rate $\times$ Gen Age</td>
<td></td>
<td>-0.005*** (0.001)</td>
</tr>
<tr>
<td>PC Growth Rate $\times$ Gen Age$^2$</td>
<td></td>
<td>0.000*** (0.000)</td>
</tr>
<tr>
<td>I(Cartel)$_4$</td>
<td>-0.939*** (0.248)</td>
<td>-0.739*** (0.239)</td>
</tr>
<tr>
<td>I(Cartel)$_{16}$</td>
<td>-0.187 (0.198)</td>
<td>-0.031 (0.191)</td>
</tr>
<tr>
<td>I(Cartel)$_{64}$</td>
<td>2.048*** (0.197)</td>
<td>1.681*** (.191)</td>
</tr>
<tr>
<td>I(Cartel)$_{128}$</td>
<td>3.531*** (0.234)</td>
<td>2.539*** (0.236)</td>
</tr>
<tr>
<td>I(Cartel)$_{256}$</td>
<td>1.629*** (0.300)</td>
<td>.779*** (0.295)</td>
</tr>
</tbody>
</table>

| R$^2$ | 0.955 | 0.958 |
| N    | 2,992 | 2,992 |

$***p < 0.01$, $**p < 0.05$, $^*p < 0.1$. The dependent variable is logged firm-level output of DRAM units, by quarter. Firm- and generation-age represent the elapsed quarters since the firm (generation) registered positive output. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Interactions of PC Growth Rate capture the differential effect PC growth on shipments over the early, peak, and post-peak phases of the product cycle. I(Cartel)$_k$ estimates the average change in output for generation $k$ during the cartel period.
Table 2: Log Output of Cartel Firms with Implied Capacity Levels, 1988-2011

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm Age</td>
<td>0.189***</td>
<td>0.176***</td>
<td>0.179***</td>
<td>0.181***</td>
</tr>
<tr>
<td>Firm Age(^2)</td>
<td>-0.003***</td>
<td>-0.002***</td>
<td>-0.003***</td>
<td>-0.003***</td>
</tr>
<tr>
<td>Gen Age</td>
<td>0.326***</td>
<td>0.337***</td>
<td>0.330***</td>
<td>0.321***</td>
</tr>
<tr>
<td>Gen Age(^2)</td>
<td>-0.005***</td>
<td>-0.005***</td>
<td>-0.005***</td>
<td>-0.005***</td>
</tr>
<tr>
<td>Time Trend</td>
<td>0.040***</td>
<td>0.041***</td>
<td>0.037***</td>
<td>0.037***</td>
</tr>
<tr>
<td>PC Growth Rate</td>
<td>0.125***</td>
<td>0.125***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Growth Rate (\times) Gen Age</td>
<td>-0.005***</td>
<td>-0.005***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Growth Rate (\times) Gen Age(^2)</td>
<td>0.000***</td>
<td>0.000***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Capacity</td>
<td>0.059**</td>
<td>0.059**</td>
<td>0.070***</td>
<td>0.566***</td>
</tr>
<tr>
<td>Implied Capacity (\times) Gen Age</td>
<td>.</td>
<td>-0.027***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied Capacity (\times) Gen Age(^2)</td>
<td>.</td>
<td>.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I(Cartel)(_4)</td>
<td>-1.034***</td>
<td>-0.861***</td>
<td>-0.648***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.251)</td>
<td>(0.242)</td>
<td>(0.243)</td>
<td></td>
</tr>
<tr>
<td>I(Cartel)(_{16})</td>
<td>-0.291</td>
<td>-0.158</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.196)</td>
<td>(.197)</td>
<td></td>
</tr>
<tr>
<td>I(Cartel)(_{64})</td>
<td>1.940***</td>
<td>1.548***</td>
<td>1.362***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.201)</td>
<td>(0.195)</td>
<td>(.198)</td>
<td></td>
</tr>
<tr>
<td>I(Cartel)(_{128})</td>
<td>3.422***</td>
<td>2.401***</td>
<td>1.834***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.238)</td>
<td>(0.240)</td>
<td>(.256)</td>
<td></td>
</tr>
<tr>
<td>I(Cartel)(_{256})</td>
<td>1.519***</td>
<td>0.640**</td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.303)</td>
<td>(.299)</td>
<td>(0.314)</td>
<td></td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.951</td>
<td>0.955</td>
<td>0.958</td>
<td>0.959</td>
</tr>
<tr>
<td>N</td>
<td>2,517</td>
<td>2,992</td>
<td>2,992</td>
<td>2,992</td>
</tr>
</tbody>
</table>

\(***p < 0.01, **p < 0.05, *p < 0.1\). The dependent variable is logged firm-level output of DRAM units, by quarter, among cartel participants. Firm- and generation-age represent the elapsed quarters since the firm (generation) registered positive output. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Implied Capacity is the average rate of change, over the most recent three quarters, of the difference between the log Moore’s Law price index and the log DRAM aggregate price/MB. Interactions of PC Growth Rate and Implied Capacity capture the differential effect PC growth (capacity level) on shipments over the early, peak, and post-peak phases of the product cycle. I(Cartel)\(_k\) estimates the average change in output for generation \(k\) during the cartel period. Standard errors are reported only for I(Cartel)\(_k\) in order to facilitate display.
**Table 3: Log Module Price Level on Covariates, 1988-2011**

<table>
<thead>
<tr>
<th></th>
<th>4Mb</th>
<th>16Mb</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>6.360***</td>
<td>5.088***</td>
</tr>
<tr>
<td></td>
<td>(0.501)</td>
<td>(0.833)</td>
</tr>
<tr>
<td><strong>Log Gen Age</strong></td>
<td>-1.551***</td>
<td>-1.218***</td>
</tr>
<tr>
<td></td>
<td>(0.131)</td>
<td>(0.218)</td>
</tr>
<tr>
<td><strong>PC Growth Rate</strong></td>
<td>0.502**</td>
<td>10.214</td>
</tr>
<tr>
<td></td>
<td>(0.234)</td>
<td>(7.124)</td>
</tr>
<tr>
<td><strong>PC Growth Rate × Gen Age</strong></td>
<td>-0.367</td>
<td>-0.500</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(0.339)</td>
</tr>
<tr>
<td><strong>PC Growth Rate × Gen Age²</strong></td>
<td>0.003</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(.005)</td>
</tr>
<tr>
<td><strong>I(Cartel)</strong></td>
<td>0.067</td>
<td>0.081</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.078)</td>
</tr>
<tr>
<td><strong>Quarters</strong></td>
<td>34-57</td>
<td>34-57</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>173</td>
<td>173</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.477</td>
<td>0.490</td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05, *p < 0.1. The dependent variable is logged industry-level deflated price in USD, by generation and quarter. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Interactions of PC Growth Rate capture the differential effect of PC growth on DRAM price over the early, peak, and post-peak phases of the product cycle. I(Cartel) estimates the average change in price for the generation in question during the cartel period.
Table 4: Log Module Price Level on Covariates, 1988-2011

<table>
<thead>
<tr>
<th></th>
<th>64Mb</th>
<th>128Mb</th>
<th>256Mb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>7.789***</td>
<td>7.131***</td>
<td>5.775***</td>
</tr>
<tr>
<td></td>
<td>(0.306)</td>
<td>(0.567)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>Log Gen Age</td>
<td>-2.134***</td>
<td>-1.910***</td>
<td>-1.393***</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.193)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>PC Growth Rate</td>
<td>3.908***</td>
<td>5.150*</td>
<td>4.258***</td>
</tr>
<tr>
<td></td>
<td>(0.478)</td>
<td>(3.031)</td>
<td>(0.595)</td>
</tr>
<tr>
<td>PC Growth Rate × Gen Age</td>
<td>0.009</td>
<td>0.725***</td>
<td>0.725***</td>
</tr>
<tr>
<td></td>
<td>(0.296)</td>
<td>(0.260)</td>
<td>(0.260)</td>
</tr>
<tr>
<td>PC Growth Rate × Gen Age²</td>
<td>-0.003</td>
<td>-0.035***</td>
<td>-0.035***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>I(Collusion)</td>
<td>-0.172*</td>
<td>-0.214</td>
<td>-1.082***</td>
</tr>
<tr>
<td></td>
<td>(0.170)</td>
<td>(0.174)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>2-Sided Eq. Test w/ 4Mb</td>
<td>(**)</td>
<td>(**)</td>
<td>(**)</td>
</tr>
<tr>
<td>2-Sided Eq. Test w/ 16Mb</td>
<td>(**)</td>
<td>(**)</td>
<td>(**)</td>
</tr>
<tr>
<td>2-Sided Eq. Test w/ 64Mb</td>
<td>(**)</td>
<td>(**)</td>
<td>(**)</td>
</tr>
</tbody>
</table>

Quarters 7-30 7-30 1-23 1-23 1-23 1-23
N 196 196 173 173 170 170
R² 0.722 0.747 0.720 0.776 0.763 0.789

***p < 0.01, **p < 0.05, *p < 0.1. The dependent variable is logged industry-level deflated price in USD, by generation and quarter. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Interactions of PC Growth Rate capture the differential effect of PC growth on DRAM price over the early, peak, and post-peak phases of the product cycle. I(Cartel) estimates the average change in price for the generation in question during the cartel period. The bottom three rows display p-values from a two-sided test of equality of the cartel coefficient between generations in the full specification.
Table 5: Log Module Price Trend on Covariates, 1988-2011

<table>
<thead>
<tr>
<th></th>
<th>(1) All Generations</th>
<th>(2) 128Mb Omitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.639*** (0.117)</td>
<td>5.906*** (0.116)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Gen Age</td>
<td>-1.382*** (0.034)</td>
<td>-1.450*** (0.034)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Growth Rate</td>
<td>5.910*** (0.584)</td>
<td>5.547*** (0.573)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Growth Rate × Gen Age</td>
<td>-0.141*** (0.029)</td>
<td>-0.136*** (0.028)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC Growth Rate × Gen Age^2</td>
<td>0.0006* (0.0003)</td>
<td>0.001** (0.0003)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I(Coll)</td>
<td>-1.080*** (0.200)</td>
<td>-0.912*** (0.216)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I(Coll) × Log Gen Age</td>
<td>0.334*** (0.062)</td>
<td>0.294*** (0.065)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N</th>
<th>580</th>
<th>525</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.907</td>
<td>0.921</td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05, *p < 0.1. The dependent variable is logged industry-level deflated price in USD, by generation and quarter. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Interactions of PC Growth Rate capture the differential effect of PC growth on DRAM price over the early, peak, and post-peak phases of the product cycle. I(Cartel) estimates the average price change attributed to cartelization at the first period of a generation’s product cycle. I(Cartel) × Log Gen Age estimates the average price trend attributable to cartelization during a generation’s product cycle.
Figure 1: Timing of Product Life Cycles and Learning
Figure 2: Collusion on \( o \) Affects Demand for \( n \)
Figure 3: Events During Cartel Period
Sources: Noll (2014), DOJ and EC Press Releases, and US Indirect Purchaser litigation

Figure 4: DRAM Module Log Price Trends By Generation

Log DRAM Module Price by Generation, 1988-2011
Log Aggregate DRAM Price/MB, 1988-2011

Figure 5: Overall DRAM Price Trend with Cartel Periods

Aggregate DRAM Price/MB Change
And Quarterly Worldwide PC Shipment Change, 1988-2011

Figure 6: Aggregate DRAM Price Change against PC Shipment Change
Figure 7: DRAM Output by Generation, First 12 Quarters

Figure 8: Derivation of Capacity Values
Figure 9: DRAM Price/MB Trend During First Cartel Period

Figure 10: DRAM Price/MB Trend From First to Second Cartel Period
Figure 11: Estimated Competitive and Cartel Price Trends
Appendices

A  Collusion with Multiproduct Punishments

This section allows firms to coordinate collusive strategies across separate product generations linked by demand substitution. It shows that multiproduct punishment may increase the scope for collusion, depending on the level of the firm-invariant discount factor $\delta$, but that collusion is never more sustainable on both generations under a multiproduct strategy as it is for generation $o$ under a single-product strategy.

Specifically, consider the strategy in which each firm maximizes the discounted sum of joint profits at $\tau$ but punishes deviation in generation $k$ with Cournot reversion in $k$ and $-k$. Call this strategy $\sigma''_i$. When punishments occur across generations, firm $i$ will consider either adhering to the collusive path on both generations or deviating from the collusive path on both generations. Deviation on one and adherence on the other is strictly dominated by deviation on both, because $i$ knows that deviation on one will be met with punishment on both generations.

Define the incentive compatibility constraints corresponding to single-product collusion, 3, as $g_o(\delta)$ and $g_n(\delta)$ when $k = o$ and $k = n$, respectively. The only difference between single- and multiproduct punishments is that firms can pool IC constraints between generations in the multiproduct case. To sustain collusion under $\sigma''_i$, firm $i$ must satisfy:

$$\sum_{k=0}^{n} \sum_{t=\tau+1}^{\infty} \delta^{t-\tau} (\Pi_{ikt}^* (\cdot) - \Pi_{ikt}^* (\cdot)) \geq \sum_{k=0}^{n} (\Pi_{ikr}^* (q_{ikr}^*, q_{jkrt}^*, q_{-krt}^*) - \Pi_{ikr}^* (\cdot))$$

$$g_o(\delta) + g_n(\delta) \geq 0$$

$$g_o(\delta) \geq -g_n(\delta)$$

Pooling IC constraints implies that collusion at the joint profit maximizing value is sustainable only if the sum of the individual IC constraints across generations (rather than each constraint individually) is greater than or equal to zero. If $\delta > \hat{\delta}_{or}$, there is “complementary slack” on the $o$ constraint that can be

---

48The analysis mirrors the treatment of multimarket collusion in Bernheim and Whinston (1990) and subsequent papers.
redistributed to the $n$ constraint. If the slack $g_o(\delta)$ is sufficiently large relative to (negative) slack $-g_n(\delta)$, then this “slack enforcement power” is sufficient to sustain collusion on both generations.

This logic leads to the following result:

**Proposition A1.** Define $\hat{\delta}_t$ as the minimum discount factor that satisfies $\sigma''_i$’s ICC at $t$.

If demand is symmetric between generations, fixed across time, and log-linear, then $\hat{\delta}_t \in (\hat{\delta}_{oT}, \hat{\delta}_{nT})$.

**Proof.** See Appendix C.2.

Result A1 assumes the same sufficient conditions as Proposition 1 and contains two implications. First, the $\sigma''_i$ minimum discount factor is bounded weakly to the left by the $\sigma'_i$ minimum discount factor for $o$. Collusion on both generations under $\sigma''_i$ is therefore less sustainable than collusion on generation $o$ under $\sigma'_i$.

Second, the minimum discount factor is bounded weakly to the right by the $\sigma'_i$ minimum discount factor for $n$. Collusion on both generations under $\sigma''_i$ is therefore more sustainable than collusion on both generations under $\sigma'_i$.

With multiproduct punishments, firms can use slack enforcement power from the incentive compatibility constraint on $o$ to enforce collusion on $n$ only if $o$’s incentive compatibility constraint has enough slack. The amount of slack depends on the level of the discount factor. Thus the imbalance between minimum discount thresholds necessary to sustain collusion may be reduced, but it cannot be completely eliminated. Moreover, for $\delta \in (\hat{\delta}_{oT}, \hat{\delta}_T)$, $\sigma''_i$ is unsustainable, $\sigma'_i$ is sustainable for $o$, and $\sigma'_i$ is unsustainable for $n$. 


B DRAM Output by Technology

Section 3 describes the rival technologies available to DRAM manufacturers during the early 2000s. DDR, developed cooperatively by DRAM fabricators through JEDEC, faced a rival technology in RDRAM, licensed by the design firm Rambus. Although RDRAM boasted slightly faster performance speeds than DDR, the two technologies were largely substitutable. After initial backing from Intel, RDRAM failed to gain popularity among fabricators and OEM’s and DDR quickly became the industry standard upon which subsequent innovations have been based.

The empirical pattern of positive cartel price effect for the 4Mb and 16Mb generations but zero or negative overcharges for the 64Mb, 128Mb, and 256Mb generations cannot be explained by changes in the underlying technology of the chips. During the 1990s, the four largest firms—Samsung, Infineon, Micron and Hynix—designed their plants to accommodate both technology types for 128Mb and 256Mb chips, skipping the older two generations.49 After DDR became the dominant next-generation technology, Rambus filed a private antitrust suit in 2004 accusing the DRAM manufacturers of flooding the market with DDR to price out RDRAM.50 Note that this case is distinct from both the DOJ antitrust case around which this paper focuses and the string of largely successful Rambus patent infringement suits that spurred the FTC and EC to file retaliatory “patent ambush” litigation.

Figures B1 and B2 display the output shares of all technologies, by DRAM generation, for the 128Mb and 256 Mb generations beginning from the cartel period through 2011. The cartel period is outlined with a dotted line. In both generations, DDR did not gain any market share until after the first 12 quarters of cartel activity concluded. RDRAM had only insignificant amounts of market share over the same period. These figures rule out the possibility that competition between firms pushing either of these technologies contributed to the output increase discussed in section 5.1, because RDRAM and DDR did not proliferate until the post-cartel period.

50 The case proceeded to a $3.95 billion trial in 2011, where a jury ultimately rejected Rambus’ allegation. See “Rambus Loses Antitrust Lawsuit, Shares Plunge,” http://www.reuters.com/article/2011/11/16/us-rambus-micron-verdict-idUSTRE7AF1L20111116
Figure B1: 128Mb DRAM Technology Share, 1998-2011

Figure B2: 256Mb DRAM Technology Share, 1999-2011
C Proofs of Results

C.1 Proof of Proposition 1

Separate the ICC for collusion on generations $k \in \{x, y\}$ into three parts, as follows:

$$
\delta \left[ (\Pi_{ik\tau+1}^{**} (\cdot) - \Pi_{ik\tau+1}^{*} (\cdot)) \right] + \sum_{t=\tau+2}^{\infty} \delta^{t-\tau} (\Pi_{ikt}^{**} (\cdot) - \Pi_{ikt}^{*} (\cdot)) > \Pi_{ik\tau}^{*} (q_{ik\tau}^{*}, q_{jk\tau}^{*}, q_{-k\tau}^{*}; s_{t}) - \Pi_{ik\tau}^{*} (\cdot)
$$

By construction, Part II and Part III are increasing in $\delta$, and it follows that there is a critical discount factor $\hat{\delta}_{kt}$ such that collusion is sustainable for $\delta \geq \hat{\delta}_{kt}$ and collusion is unsustainable for $\delta < \hat{\delta}_{kt}$.

First, consider Part III. Both generations are in the post-learning phase of their product life cycles, when cost has reached its minimum $c$: when $k = o$, $c_{iot} = c$; when $k = n$, $c_{i}\text{nt} = c$. This can be stated as:

$$
[c_{i}\text{ot} | k = o] = [c_{\text{int}} | k = n] = c
$$

(13)

Symmetric demand between generations $o$ and $n$ implies that:

$$
\left[ \begin{array}{c}
P_{ot} + \frac{\partial P_{ot}}{\partial q_{i}\text{ot}} q_{i}\text{ot} + \frac{\partial P_{nt}}{\partial q_{i}\text{nt}} Q_{nt} \\
\frac{\partial q_{i}\text{ot}}{\partial q_{i}\text{nt}} Q_{nt} \\
\frac{\partial q_{i}\text{nt}}{\partial q_{i}\text{ot}} Q_{nt}
\end{array} \right]_{MR_{i}\text{ot} | k = o} = \left[ \begin{array}{c}
P_{nt} + \frac{\partial P_{nt}}{\partial q_{i}\text{nt}} q_{i}\text{nt} + \frac{\partial P_{ot}}{\partial q_{i}\text{ot}} Q_{ot} \\
\frac{\partial q_{i}\text{nt}}{\partial q_{i}\text{nt}} Q_{nt} \\
\frac{\partial q_{i}\text{nt}}{\partial q_{i}\text{nt}} Q_{nt}
\end{array} \right]_{MR_{i}\text{nt} | k = n}
$$

(14)

Together, 13 and 14 imply the following two equalities:

$$
(q_{i}\text{ot}^{*} (\cdot), q_{i}\text{nt}^{*} (\cdot) | k = o) = (q_{i}\text{nt}^{*} (\cdot), q_{i}\text{ot}^{*} (\cdot) | k = n)
$$

(15)

Moreover, 13 and 15 imply:

$$
[\Pi_{i\text{ot}}^{**} (\cdot) - \Pi_{i\text{ot}}^{*} (\cdot) | k = o] = [\Pi_{i\text{ot}}^{**} (\cdot) - \Pi_{i\text{nt}}^{*} (\cdot) | k = n] \ \forall \ t \in \{\tau + 2, \ldots\}
$$

(16)

$$
\left[ \sum_{t=\tau+2}^{\infty} \delta^{t-\tau} (\Pi_{i\text{ot}}^{**} (\cdot) - \Pi_{i\text{ot}}^{*} (\cdot)) \right]_{k = o} = \left[ \sum_{t=\tau+2}^{\infty} \delta^{t-\tau} (\Pi_{i\text{nt}}^{**} (\cdot) - \Pi_{i\text{nt}}^{*} (\cdot)) \right]_{k = n}
$$

(17)
Second, consider Part I. Generation \(o\) is at the second phase of its product life cycle, while \(n\) is at the first phase of its life cycle. Therefore \(c_{io\tau} < c_{in\tau}\) unconditionally, and it follows that:

\[
[c_{io\tau} | k = o] < [c_{in\tau} | k = n]
\]  


\[18\]

Despite differential marginal cost across generations, equality of marginal revenues (14) holds. This implies that the marginal profitability in reducing output is the same when \(k = o\) as it is when \(k = n\):

\[
\left[ \frac{\partial \pi_{io\tau}}{\partial q_{io\tau}} \bigg| k = o \right] = \left[ \frac{\partial \pi_{in\tau}}{\partial q_{in\tau}} \bigg| k = n \right]
\]


\[19\]

Furthermore, iso-elastic demand implies that the total profitability in reducing output from the joint profit maximizing equilibrium to the Cournot equilibrium is the same when \(k = o\) as it is when \(k = n\):

\[
\left[ \int_{q_{io\tau}^{**}}^{q_{io\tau}^{*}} \frac{\partial \pi_{io\tau}}{\partial q_{io\tau}} dq \bigg| k = o \right] = \left[ \int_{q_{in\tau}^{**}}^{q_{in\tau}^{*}} \frac{\partial \pi_{in\tau}}{\partial q_{in\tau}} dq \bigg| k = n \right]
\]

\[
\left[ \Pi_{io\tau}^{*} (\cdot) - \Pi_{io\tau}^{**} (\cdot) \bigg| k = o \right] = \left[ \Pi_{in\tau}^{*} (\cdot) - \Pi_{in\tau}^{**} (\cdot) \bigg| k = n \right]
\]


\[20\]

\[21\]

Finally, consider Part II and assume for the sake of contradiction that:

\[
\left[ (\Pi_{io\tau+1}^{**} (\cdot) - \Pi_{io\tau+1}^{*} (\cdot)) \bigg| k = o \right] = \left[ (\Pi_{in\tau+1}^{**} (\cdot) - \Pi_{in\tau+1}^{*} (\cdot)) \bigg| k = n \right]
\]


\[22\]

Equality 22 implies:

\[
\left[ (P_{io\tau+1}^{**} (\cdot) - c_{io\tau+1} \cdot q_{io\tau+1}^{*} (\cdot)) \cdot q_{io\tau+1}^{**} (\cdot) \bigg| k = o \right] = \\
\left[ (P_{in\tau+1}^{**} (\cdot) - c_{in\tau+1} (q_{in\tau}^{**} (\cdot))) \cdot q_{in\tau+1}^{**} (\cdot) - (P_{in\tau+1}^{*} (\cdot) - c_{in\tau+1} (q_{in\tau}^{*} (\cdot))) \cdot q_{in\tau+1}^{*} (\cdot) \bigg| k = n \right]
\]


\[23\]
By the same logic as in Part I—cost asymmetry between generations (18) and symmetric iso-elastic demand—equality 23 implies that \( c_{\tau+1} (q_{\tau+1}^{**} (\cdot)) = c_{\tau+1} (q_{\tau+1}^{*} (\cdot)) \). However, \( q_{\tau+1}^{**} (\cdot) < q_{\tau+1}^{*} (\cdot) \) implies:

\[
\begin{align*}
  c_1 \cdot f (q_{\tau+1}^{**} (\cdot)) & > c_1 \cdot f (q_{\tau+1}^{*} (\cdot)) \\
  c_{\tau+1} (q_{\tau+1}^{**} (\cdot)) & > c_{\tau+1} (q_{\tau+1}^{*} (\cdot))
\end{align*}
\] (24)

\[
\begin{align*}
  c_{\tau+1} (q_{\tau+1}^{**} (\cdot)) & > c_{\tau+1} (q_{\tau+1}^{*} (\cdot))
\end{align*}
\] (25)

It follows that the profits from colluding at \( \tau + 1 \) are greater when \( k = o \) than when \( k = n \):

\[
\begin{align*}
  \left[ (\Pi_{\tau+1}^{**} (\cdot) - \Pi_{\tau+1}^{*} (\cdot)) \right. & < \left. (\Pi_{\tau+1}^{**} (\cdot) - \Pi_{\tau+1}^{*} (\cdot)) \right] \\
  k = o & < k = n
\end{align*}
\] (26)

Combining 17, 21, and 26, it follows that the minimum discount factor necessary for collusion when \( k = o \) is lower than the minimum discount factor necessary for collusion when \( k = n \):

\[
\hat{\delta}_{\tau+1} < \hat{\delta}_{\tau+1}
\] (27)
C.2 Proof of Proposition A.1

Recall that appendix C.1 proves that \( \hat{\delta}_n > \hat{\delta}_o \). Also recall from Appendix A that the pooled ICC corresponding to \( \sigma_i'' \) is:

\[
g_o(\delta) \geq -n(\delta)
\]  

(28)

The proof is divided into two parts to correspond to two distinct cases. First, I show that \( \hat{\delta}_r \) is strictly greater than \( \hat{\delta}_o \). Consider increasing \( \delta \) from the left. As \( \delta \to \hat{\delta}_o \) from the left, \( g_o(\cdot) \to 0 \) from the left and 28 is unsatisfied:

\[
\lim_{\delta \to \hat{\delta}_o} g_o(\delta) = 0
\]  

(29)

\[
\lim_{\delta \to \hat{\delta}_o} g_o(\delta) + n(\delta) < 0
\]  

(30)

\[
\lim_{\delta \to \hat{\delta}_o} g_o(\delta) < -n(\delta)
\]  

(31)

And it follows that \( \hat{\delta}_r > \hat{\delta}_o \).

Second, I show that \( \hat{\delta}_r \) is strictly less than \( \hat{\delta}_n \). Consider the range \( \hat{\delta}_o < \delta < \hat{\delta}_n \). Define \( g_o(\hat{\delta}_n) - g_o(\hat{\delta}_o) = \gamma > 0 \). As \( \delta \to \hat{\delta}_n \) from the left, \( g_n(\cdot) \to 0 \) from the left and 28 is satisfied:

\[
\lim_{\delta \to \hat{\delta}_n} g_n(\delta) = 0
\]  

(32)

\[
\lim_{\delta \to \hat{\delta}_n} g_o(\delta) + g_n(\delta) = \gamma + 0
\]  

(33)

\[
\lim_{\delta \to \hat{\delta}_n} g_o(\delta) - \gamma = -g_n(\delta)
\]  

(34)
Define $\epsilon > 0$ as an arbitrarily small constant. By the continuity of $g_\alpha(\cdot)$, there exists an $\epsilon$ such that:

\[
g_\alpha(\hat{\delta}_{n\tau}) - g_\alpha(\hat{\delta}_{n\tau} - \epsilon) \leq \gamma \tag{35}
\]

\[
g_\alpha(\hat{\delta}_{n\tau} - \epsilon) \geq g_\alpha(\hat{\delta}_{n\tau}) - \gamma = -g_n(\hat{\delta}_{n\tau}) \geq -g_n(\hat{\delta}_{n\tau} - \epsilon) \tag{36}
\]

And it follows that $\hat{\delta}_r < \hat{\delta}_{n\tau}$. ■
C.3 Proof of Proposition 2

Consider firm $i$’s first order condition for generation $n$ at period $\tau$ and rewrite it as follows. For notational convenience, the time subscript is dropped except where the period is $\tau + 1$:

$$P_n + \frac{\partial P_n}{\partial q_{in}} q_{in} = \frac{\partial C_{in}}{\partial q_{in}} + \delta \frac{\partial C_{in\tau+1}}{\partial q_{in}} \cdot q_{in\tau+1} - \frac{\partial P_o}{\partial q_{in}} \cdot q_{io}$$  \hspace{1cm} (38)

$$q_{in} = -\frac{\partial P_o}{\partial q_{io}} \cdot q_{io} - P_n \frac{\partial q_{in}}{\partial P_n} + c_1 \frac{\partial q_{in}}{\partial P_n} + \left( \delta c_1 \frac{\partial f}{\partial q_{in}} \cdot q_{in\tau+1} \right) \frac{\partial q_{in}}{\partial P_n}$$  \hspace{1cm} (39)

Assume first that demand is linear. To gauge $i$’s response on generation $n$ to a change in the output of generation $o$, differentiate 39 with respect to $q_{io}$:

$$\frac{\partial q_{in}}{\partial q_{io}} = -\frac{\partial P_o}{\partial q_{io}} \cdot \frac{\partial q_{io}}{\partial q_{in}} - \frac{\partial q_{in}}{\partial P_n} \frac{\partial P_n}{\partial q_{io}} < 0$$  \hspace{1cm} (40)

Linear demand renders all second derivatives with respect to $q_{io}$ zero. Each remaining partial derivative expression is negative by downward-sloping demand, so $\frac{\partial q_{in}}{\partial q_{io}} < 0 \Rightarrow o$ and $n$ are strategic substitutes.

Assume instead that demand is log-linear. Differentiating 39 with respect to $q_{io}$ yields:

$$\frac{\partial q_{in}}{\partial q_{io}} = -\frac{\partial^2 P_o}{\partial q_{io}^2} \frac{\partial q_{io}}{\partial q_{in}} q_{io} - \frac{\partial P_o}{\partial q_{io}} \frac{\partial q_{io}}{\partial P_n} - \frac{\partial P_n}{\partial q_{io}} \frac{\partial q_{in}}{\partial P_n} - P_n \frac{\partial^2 q_{in}}{\partial P_n \partial q_{io}} \overset{>0}{=}$$  \hspace{1cm} (41)

$$\frac{\partial q_{in}}{\partial q_{io}} < 0 \Leftrightarrow -\frac{\partial^2 P_o}{\partial q_{io}^2} \frac{\partial q_{io}}{\partial q_{in}} q_{io} < \frac{\partial P_o}{\partial q_{io}} \frac{\partial q_{io}}{\partial P_n} + \frac{\partial P_n}{\partial q_{io}} \frac{\partial q_{in}}{\partial P_n} + P_n \frac{\partial^2 q_{in}}{\partial P_n \partial q_{io}} \overset{>0}{=}$$  \hspace{1cm} (42)

Log-linearity implies that the first underbraced expression in 42 is positive: $n$’s (unstandardized) inverse own-price demand slopes downward at a decreasing rate. Similarly, the second underbraced expression in 42
is positive because the slope of $n$’s inverse own-price demand increases as $q_{io}$ increases.

\[
\ln(p_n) = a - \eta \ln(Q_n) - \gamma \ln(Q_o)
\]  

(43)

\[
Q_n = \exp \left\{ \frac{a}{\eta} - \frac{\ln(P_n)}{\eta} - \frac{\gamma}{\eta} \ln(Q_o) \right\}
\]  

(44)

\[
\frac{\partial Q_n}{\partial P_n} = \exp \left\{ \frac{a}{\eta} - \frac{\ln(P_n)}{\eta} - \frac{\gamma}{\eta} \ln(Q_o) \right\} \cdot -\frac{1}{\eta P_n} < 0
\]  

(45)

\[
\frac{\partial Q_n^2}{\partial P_n Q_o} = \exp \left\{ \frac{a}{\eta} - \frac{\ln(P_n)}{\eta} - \frac{\gamma}{\eta} \ln(Q_o) \right\} \cdot \frac{\gamma}{\eta^2 P_n Q_o} > 0
\]  

(46)

Therefore the sufficient condition for intergenerational strategic substitution, 42, requires that generation $n$’s demand curve does not flatten out significantly faster as $Q_n$ increases than as $Q_o$ increases. This condition is likely to be satisfied along the demand curve for most plausible specifications.

Inequalities 40 and 42 show that firm $i$’s response on generation $n$ to a decrease (increase) in the output of generation $o$ is positive (negative). It follows that $i$’s output of generation $n$ is greater under the set of strategies $\Theta^{**}$ than under the set of strategies $\Theta^*$, and through $i$’s symmetry with $j$, the same holds with respect to total output:

\[
q_{io}^*(q_{in}(\cdot)) < q_{io}^*(q_{in}(\cdot)) \Rightarrow q_{in}^*(q_{io}^{**}(\cdot)) > q_{in}^*(q_{io}^*(\cdot))
\]  

(47)

\[
\Rightarrow Q_n^*(Q_o^{**}(\cdot)) > Q_n^*(Q_o^*(\cdot))
\]  

(48)
## D Additional Tables

### Table D1: Log Module Price Level on Covariates and Implied Capacity, 1988-2011

<table>
<thead>
<tr>
<th></th>
<th>4Mb</th>
<th>16Mb</th>
<th>64Mb</th>
<th>128Mb</th>
<th>256Mb</th>
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<tbody>
<tr>
<td>Intercept</td>
<td>5.103***</td>
<td>2.840***</td>
<td>7.172***</td>
<td>5.649***</td>
<td>5.734***</td>
</tr>
<tr>
<td></td>
<td>(0.834)</td>
<td>(0.776)</td>
<td>(0.566)</td>
<td>(0.224)</td>
<td>(0.226)</td>
</tr>
<tr>
<td>Log Gen Age</td>
<td>-1.224***</td>
<td>-0.595***</td>
<td>-1.916***</td>
<td>-1.312***</td>
<td>-1.340***</td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
<td>(0.220)</td>
<td>(.192)</td>
<td>(0.095)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>PC Growth Rate</td>
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<td>12.889**</td>
<td>5.026*</td>
<td>1.932</td>
<td>1.653</td>
</tr>
<tr>
<td></td>
<td>(7.130)</td>
<td>(5.974)</td>
<td>(3.026)</td>
<td>(1.604)</td>
<td>(1.568)</td>
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<tr>
<td>PC Growth Rate × Gen Age</td>
<td>-.361</td>
<td>-.494</td>
<td>-.001</td>
<td>0.719***</td>
<td>0.726***</td>
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<tr>
<td></td>
<td>(.313)</td>
<td>(0.339)</td>
<td>(0.295)</td>
<td>(.260)</td>
<td>(0.255)</td>
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<td>PC Growth Rate × Gen Age²</td>
<td>.003</td>
<td>.004</td>
<td>-.003</td>
<td>-.035***</td>
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<td></td>
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<td>(0.004)</td>
<td>(0.007)</td>
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<td>-.039</td>
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<td>(.013)</td>
<td>(0.018)</td>
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<tr>
<td>I(Collusion)</td>
<td>.061</td>
<td>.212*</td>
<td>-.135</td>
<td>-1.107***</td>
<td>-0.191</td>
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<td></td>
<td>(0.081)</td>
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<td>(0.182)</td>
<td>(0.201)</td>
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<table>
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<th></th>
<th>2-Sided Eq. Test w/ 4Mb</th>
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<tr>
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<td>173</td>
<td>197</td>
<td>196</td>
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<td>R²</td>
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<td>0.400</td>
<td>0.730</td>
<td>0.776</td>
<td>0.790</td>
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***p < 0.01, **p < 0.05, *p < 0.1. The dependent variable is logged industry-level deflated price in USD, by generation and quarter. PC Growth Rate measures the year-over-year change in worldwide PC shipments. Implied Capacity is the average rate of change, over the most recent three quarters, of the difference between the log Moore’s Law price index and the log DRAM aggregate price/MB. Interactions of PC Growth Rate capture the differential effect of PC growth on DRAM price over the early, peak, and post-peak phases of the product cycle. I(Cartel) estimates the average change in price for the generation in question during the cartel period (interactions of Implied Capacity with generation age are insignificant). The bottom three rows display p-values from a two-sided test of equality of the cartel coefficient between generations in the full specification.
Table D2: DRAM Years Active
by Generation, 1974-2011

<table>
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<th>Generation</th>
<th>Years Active*</th>
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<tbody>
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<td>4Kb(^1)</td>
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</tr>
<tr>
<td>16Kb</td>
<td>1976-1985</td>
</tr>
<tr>
<td>64Kb</td>
<td>1979-1995</td>
</tr>
<tr>
<td>256Kb</td>
<td>1982-1997</td>
</tr>
<tr>
<td>1Mb</td>
<td>1985-2002</td>
</tr>
<tr>
<td>4Mb</td>
<td>1988-2010</td>
</tr>
<tr>
<td>16Mb</td>
<td>1991-2011</td>
</tr>
<tr>
<td>64Mb</td>
<td>1996-2011</td>
</tr>
<tr>
<td>128Mb</td>
<td>1998-2011</td>
</tr>
<tr>
<td>256Mb</td>
<td>1999-2011</td>
</tr>
<tr>
<td>512Mb</td>
<td>2001-2011</td>
</tr>
<tr>
<td>1Gb</td>
<td>2003-2011</td>
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<tr>
<td>2Gb</td>
<td>2005-2011</td>
</tr>
<tr>
<td>4Gb</td>
<td>2010-2011</td>
</tr>
</tbody>
</table>

* Year is counted if at least one firm produces output in any quarter
\(^1\) First year of Gartner data: shipments began about two years earlier
Table D3: $C_4$ Concentration Ratios by Generation, 1994-2004

<table>
<thead>
<tr>
<th>Year</th>
<th>16Mb</th>
<th>64Mb</th>
<th>128Mb</th>
<th>256Mb</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>60.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>51.4</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>51.4</td>
<td>76.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>42.8</td>
<td>79.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>53.4</td>
<td>56.2</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>62.6</td>
<td>67.6</td>
<td>75.1</td>
<td>100</td>
</tr>
<tr>
<td>2000</td>
<td>66.8</td>
<td>68.7</td>
<td>76.9</td>
<td>82.6</td>
</tr>
<tr>
<td>2001</td>
<td>68.5</td>
<td>73.6</td>
<td>74.3</td>
<td>74.2</td>
</tr>
<tr>
<td>2002</td>
<td>60.5</td>
<td>72.2</td>
<td>78.2</td>
<td>77.6</td>
</tr>
<tr>
<td>2003</td>
<td>73.7</td>
<td>69.2</td>
<td>79.2</td>
<td>78.4</td>
</tr>
<tr>
<td>2004</td>
<td>79.3</td>
<td>70.3</td>
<td>77.0</td>
<td>74.7</td>
</tr>
</tbody>
</table>

* The four largest firms across generations from 1994-2004 were Samsung, Infineon, Micron and Hynix.
In addition to changes in the market shares of the four pre-existing firms, year-to-year changes reflect new firms entering a generation and merger and acquisition activity. As characterized in Gartner Research’s data: in 1998, Micron purchased Texas Instruments’ DRAM operations. In 1999, SK Hynix (then named Hyundai) merged with LG Semiconductor. In 2001, NEC and Hitachi began operating the DRAM joint venture Elpida Memory.
E  Additional Figures

Figure E1: Revenue Share: 4Mb - 256Mb
Figure E2: Cartel Insider Market Share: 4Mb - 256Mb

Figure E3: Total Output by Generation: 256 Kb - 4Gb