A Dynamic Analysis of Cooperative Research in the Semiconductor Industry

Minjae Song*

Simon Graduate School of Business, University of Rochester

July 2010

Abstract

In this paper I construct a dynamic oligopolistic model of research joint ventures (RJVs). In my model, when firms form an RJV, they invest to improve product quality, and fully share the rewards of research success. RJVs benefit firms by eliminating duplicative research efforts, but firms also give up the possibility of becoming a solo innovator. Consumers benefit from lower prices, but may have to wait longer for new products to arrive. I show that RJVs are welfare enhancing by quantitatively evaluating these trade-offs with data from the semiconductor industry. I also analyze how changes in product market competition affect research cooperation.

* JEL classification numbers: C73, D92, L63, O31

Keywords: Research Joint Venture, Dynamic Model of Oligopoly, Product Innovation, Firm Heterogeneity

*Box 270100, Simon Graduate School of Business, University of Rochester, Rochester, NY 14627. Tel: (585) 275-0269 E-mail: minjae.song@simon.rochester.edu. I am grateful to Gary Chamberlain, Dale Jorgenson, Lynne Kiesling, Katz Miyagiwa, Ariel Pakes, Bernard Salanié, Ralph Siebert, Kenneth Wolpin, anonymous referees, and participants at various conferences and seminars for their suggestions and comments. All errors are mine.
1 Introduction

Firms competing in a product market often form a joint research venture (RJV) to cooperate in research and development (R&D). A prominent example is SEMATECH in the semiconductor industry where rival firms cooperate in developing photolithography technology which is one of the key generic manufacturing technologies. Examples of RJVs are also found in the automotive industry, the biopharmaceutical industry, the food and beverage industry, the paper and pulp industry, etc. While the US government prohibits firms from colluding in product markets, it allows cooperation in R&D. In fact, the National Cooperative Research Act, enacted in 1984, provides government support to RJVs.

The R&D literature argues that RJVs are welfare enhancing. A usual argument is that RJVs internalize spillover so that member firms increase their R&D spending, which in turn increases profit and consumer surplus through cost reduction (Katz, 1986; d’Aspremont and Jacquemin, 1988; Suzumura, 1992; Kamien, Muller, and Zang, 1992.) This result is contingent upon a sufficiently high spillover rate, which is defined as the rate at which a firm benefits from a rival firm’s R&D spending. For example, for an RJV to be welfare enhancing, d’Aspremont and Jacquemin (1988) need the condition that each dollar a firm spends on R&D must reduce its rival’s manufacturing cost by at least 50 cents. Kamien, Muller, and Zang (1992) define an RJV as a state where the spillover rate is at the maximum level. Numerous subsequent papers have extended and/or tested the implications of the models developed in d’Aspremont and Jacquemin (1988) and Kamien, Muller, and Zang (1992).

Models focusing on the spillover effect predict that RJVs stimulate firms to increase research efforts as long as there is enough spillover. In addition, these models predict that, barring government intervention, firms will voluntarily form RJVs, which will benefit consumers. However, to the extent that an RJV is formed to eliminate duplicative efforts, either by running a single lab instead of multiple labs or by sharing research outcomes among member firms, these models become less relevant and their predictions may not be accurate.

For example, Irwin and Klenow (1996a) compare SEMATECH members’ R&D spending with that of non-members, and show that, after controlling for firm specific variables, member companies are likely to spend less on R&D. This leads them to conclude that SEMATECH’s main role is to reduce the duplication
of R&D efforts. Since photolithography technology is both an expensive technology to develop and a generic technology that benefits the manufacturers of different types of semiconductors, member firms coordinate technology development through SEMATECH, instead of racing to develop their own technology. This process forces the member firms to share the associated research costs and outcomes.

When research cooperation is characterized by the elimination of duplicative efforts, firms face an interesting trade-off. They can reduce the development costs of a new technology, but the opportunity to become a solo innovator is lost. In other words, cooperative research can be a lower cost but smaller reward activity compared to non-cooperative research. Firms will voluntarily form an RJV only if the cost savings outweigh the foregone benefit of becoming a solo innovator.

The implications of RJVs on consumer welfare are ambiguous as well. Products are likely to be less differentiated; this benefits consumers via increased product market competition. However, due to smaller rewards, RJVs reduce the incentive for innovation. This will lead to less frequent new product introduction, which will hurt consumers. Therefore, whether RJVs are welfare enhancing depends on factors such as the magnitude of cost saving, consumers’ willingness to pay for quality improvement, and the price elasticity of demand.

In this paper I construct an RJV model where firms and consumers face the trade-offs described above, and quantitatively evaluate the welfare effects using data. I model an RJV using a structural dynamic oligopoly model developed by Ericson and Pakes (1995) and Pakes and McGuire (1994). In particular, I consider duopolists who invest to improve product quality in a differentiated product market. I define an RJV as firms sharing a research success probability, which is a function of the member firms’ research expenditure. By sharing the success probability firms share the rewards of any one member having research success.¹ The non-cooperative research regime (or the competitive research regime) is identical to the quality improving game modeled by Pakes and McGuire (1994). In both regimes firms compete à la Bertrand in the product market.²

I apply this model to the semiconductor industry and analyze research cooperation through SE-

¹My definition of RJV is similar to Choi (1993), Marjit (1991) and Combs (1992) also define RJVs in a similar manner but treat the research success probability as an exogenous parameter.

²Although I focus on the product innovation (quality improvement) in this paper, the model can be easily modified to describe the process innovation (cost reduction). In the process innovation firms are heterogenous with respect to the production cost and compete à la Cournot in the product market.
MATECH. The competitive research regime in comparison is a hypothetical regime where firms unilaterally develop the photolithography technology. I confine my product market analysis to the CPU sector where Intel and Advanced Micro Devices (AMD) are the major players.\(^3\) I use product-level data on Intel and AMD CPUs from 1993 to 2000 to estimate consumers’ willingness to pay for quality improvement and the price elasticity of demand. RJVs enhance welfare most when the price elasticity of demand is high or the willingness to pay for quality is low.

Without firm-level data on research expenditure, I cannot estimate research related parameters such as the success probability, the spillover rate, or research efficiency.\(^4\) Instead, I choose a functional form for the success probability and use the model structure and equilibrium conditions to compute the research expenditure at different parameter values. This research expenditure is then compared to the hypothetical research expenditure without SEMATECH to quantify the cost savings.

I consider two types of RJVs: RJV competition and RJV cartelization. In the RJV competition regime firms set research expenditure to maximize the discounted sum of their own profits. In the RJV cartelization regime they maximize the discounted sum of joint profit.\(^5\) It turns out that the two regimes differ in how firms divide research expenditures. In RJV cartelization firms spend equally as long as their research efficiency is the same. In RJV competition the relative size of expected gains matters. In this case a firm with a higher expected gain spends more even when the research efficiency is the same.

Since a new technology enables firms to produce a faster CPU, I use the maximum CPU speed attainable with each generation of technology as a state variable to represent technological advance in the industry. In the RJV regimes a transition to a higher maximum speed is only possible by research success through SEMATECH, and a higher maximum speed is available to both firms at the same time. Consumers’ willingness to pay for faster speed and their sensitivity to price determine the magnitude of research rewards. I estimate these rewards by employing a discrete choice model of differentiated product demand as in Berry (1994).

---

\(^3\) Firms in other sectors of the industry such as DRAM and flash memory sectors also participate to SEMATECH and produce a wide range of semiconductors using this technology. However, the CPU sector is a leading technology sector that benefits most from the advancement of photolithography technology.

\(^4\) Research efficiency represents a firm’s ability to transform research expenditure into the success probability.

\(^5\) This distinction is similar to Kamien, et.al. (1992) who consider both the unilateral and the joint profit maximization within their RJV regime.
Products of the same processing speed are still differentiated. For example, the actual performance of the same speed CPUs can differ depending on the design of transistor patterns. Therefore, I need a non-speed related variable to represent firms’ product market competitiveness. I use each firm’s mean value of “unobserved” quality. The discrete choice demand model quantifies product quality based on each product’s market share and links it to product attributes and price. The unexplained part is treated as unobserved quality, and I use its mean value to estimate the non-speed related state variable.  

My results show that research expenditure in RJV regimes is twenty five to fifty percent less than it would be in a competitive research environment. Thus, RJVs are likely to result in higher net profits as the cost savings outweigh the foregone benefit of being a solo innovator. RJV regimes are also more likely to generate higher consumer surplus as the benefit of paying lower prices for new products outweighs the benefit of having new products more frequently in the competitive research environment.

My paper is the first to explicitly model cooperative investment decisions in a dynamic oligopoly framework. Almost all empirical studies on RJVs take a reduced-form regression approach. For example, Branstetter and Sakakibara (2002) use data on a large number of Japanese research consortia to test whether RJV outcomes are correlated with R&D spillovers. They measure consortium outcomes with the number of patents registered by participating firms during and after a consortium, and use the firm proximity index developed by Jaffe (1986) to measure the level of potential R&D spillovers. Then using the difference-in-difference approach, they show that consortium outcomes are positively associated with the level of potential R&D spillovers within consortia. As discussed above, Irwin and Klenow (1996a) is the most well known empirical study on research cooperation in the semiconductor industry.

Unlike these studies, my analysis is based on a structural model that describes how firms make research decisions in different research regimes. Thus, given a firm’s regimen choice, I can compare firms’ research behavior across regimes. I can also compare welfare across the regimes and explain what drives welfare differences. Moreover, I can link firms’ research decisions to changes in a product market. For example, in the late 1990s competition between Intel and AMD became more intense. Prior to that point,

---

6I do not model how firms competitively improve unobservable characteristics. Instead I analyze how firms’ cooperative research behaviors are affected by changes in unobservable characteristics.

7I treat RJVs as an exogenous state and focus on evaluating the welfare effects of RJVs compared to having no RJVs. In doing so, I ignore an endogenous formation of RJVs.
AMD had mainly served consumers at the low end of the market. However, thanks to the success of its high-end products, AMD became an even stronger competitor for Intel. To investigate how their cooperative research activity would be affected by this change, I compare their research expenditure for two different paths of product market evolution. One path represents a market where one firm has an advantage in non-speed related product quality, whereas the other path represents neck and neck competition.

The rest of the paper is organized as follows. Section 2 describes a dynamic model of cooperative research. Section 3 provides a brief description of SEMATECH. Section 4 presents estimation and computational results. Section 5 follows with a welfare analysis. Section 6 examines how the market structure affects firms’ cooperative research behaviors. Section 7 concludes.

2 Model

2.1 Setup and Timing

In each period two firms (say, Intel and AMD) decide how much to invest in order to develop a more advanced technology (a new generation of photolithography technology) for the next period. The more advanced technology improves product quality (a faster processing speed). The outcome of research investment is assumed to be stochastic. The more firms invest in research, the higher the probability of research success. Firms share the costs and outcomes of research by having a common probability of research success.8

After making their research decision but before a research outcome is realized, firms make their own differentiated products (processors) with the current technology and compete à la Bertrand in the product market (the CPU market.) The technology they develop together is a generic manufacturing technology, so they can differentiate their products in multiple ways during the product development stage.

At the end of each period the research outcome is realized and a technology for the next period is determined. If research is successful, the firms have a more advanced technology. If not, they use the current technology in the next period.

8I assume that firms do not accumulate R&D stock even if they fail to innovate.
2.2 Probability of Research Success

I assume that the probability of research success \( f(.) \) is a continuous function of research expenditure, \( x \), with \( f'(x) > 0, f''(x) \leq 0, f(0) = 0 \) and \( \lim_{x \to \infty} f(x) = 1 \). Although any probability functions that satisfy these properties can be used, I make the following parametric assumptions for analytical and computational convenience.

**Assumption 1** Given firm \( k \)'s research expenditure, \( x_k \), the probability of firm \( j \)'s research success is

\[
f_j(x_j|x_k,a_j,a_k,\sigma) = \frac{a_jx_j + \sigma a_ja_kx_jx_k}{1 + a_jx_j + a_kx_k + \sigma a_ja_kx_jx_k},
\]

for \( j = 1, 2, k = 1, 2 \) and \( j \neq k \). \( x_j \) is firm \( j \)'s research expenditure, which takes non-negative values, \( a_j \) is firm \( j \)'s efficiency level, and \( \sigma \) denotes a degree of spillover with \( \sigma \geq 1 \).

A firm’s efficiency level, \( \alpha_j \), represents the impact of one dollar of research expenditure on the probability of research success. Thus, a more efficient firm attains a higher success probability with the same expenditure. The degree of spillover, \( \sigma \), indicates how much one firm benefits from the other firm’s research expenditure. With \( \sigma > 1 \), firm \( i \)'s success probability increases as firm \( j \) increases its expenditure. As a result, the two firms’ probabilities, i.e., \( f_1 \) and \( f_2 \), are positively correlated. When there is no spillover, the probability function becomes

\[
f_j(x_j|\sigma = 1) = \frac{a_jx_j}{1 + a_jx_j}, \quad j = 1, 2,
\]

and the two firms' probabilities are independent of each other.

**Assumption 2** When firms form a research joint venture (RJV), the success probability of cooperative research is

\[
f^J(x|a_1,a_2,\sigma) = \frac{a_1x_1 + a_2x_2 + \sigma a_1a_2x_1x_2}{1 + a_1x_1 + a_2x_2 + \sigma a_1a_2x_1x_2}.
\]

In RJVs firms share the probability of research success. Thus, with SEMATECH as a sole provider of the generic technology, all member firms simultaneously gain access to a new photolithography technology enabling them to improve their processing speeds at the same time.

Assumption 2 restricts the success probability of RJVs such that the industry-wide probability of
research success is the same whether firms compete or cooperate as long as the total research expenditure is the same. In other words, given research expenditures,

\[ f^i(x_1, x_2) = f_1(x_1, x_2) + f_2(x_1, x_2) - f_b(x_1, x_2) \]  \hspace{1cm} (4)

where \( f_b \) is the probability that both firms succeed at the same time without research cooperation. However, \( x_i \) differs depending on whether firms form an RJV. Therefore, equation (4) may not hold in equilibrium and the industry wide probability of research success may differ across the regimes.

My definition of RJVs are different from those in the R&D literature in two significant ways. First, my definition does not depend on the spillover effect. The degree of spillover \( \sigma \) is the same in equations (1) and (3). This allows me to consider the effect of sharing research costs and outcomes apart from the spillover effect. Separating the cost savings from the spillover is important as these two effects have opposite predictions for research expenditure.

Second, in my model the research intensity, which differs depending on whether firms cooperate or not, determines the probability of research success. Many studies on stochastic cooperative research adopt a fixed research intensity assumption (Marjit, 1991; Combs, 1992; Bloch and Markowitz, 1996; Miyagiwa, 2005). Under this assumption, the probability of research success is exogenously given. For example, Combs (1992) assumes that each firm faces a menu of \( m \) research projects with the success probability equal to \( 1/m \). When two firms form an RJV, they can choose two projects without replacement so that the success probability of the RJV becomes \( 2/m \). My model can replicate this by letting \( f_b(x_1, x_2) \) be zero and fixing \( x_i \) at the same level on both sides of equation 4.\(^9\)

2.3 Value Function and State Variables

Given the current period’s states, \( \omega \), the value function for firm \( j \) is defined as

\[ V_j(\omega) = \sup_{x_j \geq 0} \left[ \pi_j(\omega) - x_j + \beta \sum_{x_j' \geq 0} V_j(\omega') G(\omega'|\omega, x) \right], \text{ for } j = 1, 2, \]

\(^9\)My model does not capture all aspects of cooperative research. For example, the model does not allow any synergy that may arise in cooperative research. Although the synergy effect can be described with higher research efficiency in RJVs, i.e., higher \( a_i \) in equation (3), I do not explore this. See section 7 for more discussions on limitations of my model.
where $\pi_j$ denotes firm $j$’s variable profit, $\beta$ a discount rate, and $\omega'$ a vector of state variables in the next period. $G$ is the probability distribution which generates the transition probabilities of the states. I explain which variables are included in $\omega$ below.

The value function for a firm cooperating in research can be rewritten as

$$V_j (\omega) = \sup_{x_j \geq 0} \left[ \pi_j (\omega) - x_j + \beta \left( f^J (x|a, \sigma, \omega) \bar{EV}^s_j + (1 - f^J (x|a, \sigma, \omega)) \bar{EV}^n_j \right) \right],$$

where $\bar{EV}_j^s$ is firm $j$’s expected value conditional on successful cooperative research and $\bar{EV}_j^n$ on unsuccessful cooperative research.

When firms unilaterally invest in competitive research, the value function becomes

$$V_j (\omega) = \sup_{x_j \geq 0} \left[ \pi_j (\omega) - x_j + \beta \left( f_j (x|a, \sigma, \omega) \bar{EV}^s_j + (1 - f_j (x|a, \sigma, \omega)) \bar{EV}^n_j \right) \right],$$

where $f_j (x|a, \sigma, \omega)$ is the probability that firm $j$ succeeds in research (equation (1)), $\bar{EV}_j^s$ is firm $j$’s expected value conditional on firm $j$’s research being successful, and $\bar{EV}_j^n$ is firm $j$’s expected value conditional on firm $j$’s research being unsuccessful. Note that firm $j$ takes an expectation over firm $k$’s research outcomes in computing $\bar{EV}_j^s$ and $\bar{EV}_j^n$. Thus, firm $k$’s research expenditure affects $\bar{EV}_j^s$ and $\bar{EV}_j^n$ in competitive research.

Four state variables are used to describe industry dynamics. The first is the maximum processing speed attainable with each generation of photolithography technology. This represents SEMATECH’s path of technological advancement. A more advanced photolithography technology increases the processing speed by allowing more transistors to be inscribed. Section 3 provides more details on SEMATECH. The transition probability is endogenously determined by the firms’ research expenditures through $f^J (.)$ in equation (3).

The second state variable is non-processor speed product quality and is used to reflect a firm’s product market competitiveness. For example, Intel and AMD inscribe different patterns of transistors on the silicon wafer, and this transistor pattern determines the actual performance of the CPU. Alternatively, it could reflect differences due to advertising or marketing campaigns. I estimate this state variable using the detrended mean value of unobserved quality, which is the part of product quality not explained by observed
product attributes or price. This is basically the residual term from the demand equation.

I assume that the second state variable evolves independently of the first, but that the first evolves conditional on realizations of the second. This implies that firms take actions affecting the unobserved quality independently of their maximum processing speed levels, but account for unobserved quality in the investment decision. The second part of the assumption is innocuous because non-processor speed product quality affects the size of the research rewards.

However, the assumption that non-speed quality evolves independent of processor speed technology requires further elaboration. Take designing the transistor pattern as an example. This assumption implies that firms try to improve the design efficiency regardless of the likelihood of improving the maximum speed. It is a reasonable assumption because a more efficient design improves the processor performance at any speed level. However, the unobserved quality also includes other activities, like marketing efforts, which firms may change when expecting a new product arrival. Nevertheless, this assumption is necessary to make the computation of the dynamic model feasible and is standard in the literature (Rust, 1987; Ericson and Pakes, 1995). Following Tauchen (1986), the transition probability of the second state variable is estimated using an AR(1) model.

I treat firms as if they only produce one product that demands the most advanced technology available. I call such products frontier products. This assumption means that I ignore a multi-product feature. Although this is a limitation of the model, the single frontier product feature is a good approximation of firms’ incentives to innovate. In the CPU market, firms earn most of their profits from the frontier product by charging high prices. They still sell non-frontier products, but their prices are much lower. This means that a disproportionately large part of the rewards from research success is realized shortly after product introduction. Thus, it is not likely that this assumption has a material impact on my results.

The other two state variables describe endogenous demand fluctuations over time. One is a binary variable indicating whether there was an innovation in the previous period. The other state variable indicates total demand, defined as the number of consumers who buy products, and takes on either a high value or a low value. The total demand is different from the exogenously given market size. The total demand changes, depending on a sequence of innovations (or non innovation). In particular, it takes on a low value when
there are two consecutive innovations or two consecutive non innovations. It takes on a high value when an
innovation follows a non innovation or vice versa. Thus, the firms' incentives to innovate are much stronger
following a non innovation and weaker following an innovation.

This endogenous demand fluctuation describes, although in a limited way, a market where consumers
purchase products intermittently. Since firms have weaker incentives to innovate following a successful
innovation, they are not likely to innovate every period in equilibrium. Therefore, newly introduced products
are likely to stay in the market for multiple periods. I treat consumers who purchase new products in the
first period differently from those who purchase in the second period. The former is a type of consumer who
buys a new product immediately and the latter is a type who waits for one period. I explain how consumers
make product choices and some modelling limitations in section 2.5.

The following example illustrates what is likely to happen in an equilibrium. Suppose there was an
innovation at the end of the last period and no innovation two periods before. Then firms sell new products
to 80 percent (a high value of the total demand) of the first type of consumers during this period. However,
they do not invest aggressively and are unlikely to innovate at the end of this period. If no innovation is
achieved this period, then in the following period they sell the same products to 80 percent of the second
type of consumers. However, if they innovate this period, they will sell new (and better) products in the
following period but only to 20 percent (a low value) of the first type. Thus, firms are likely to innovate
every other period and both types of consumers are likely to purchase products every other period.\footnote{Following this logic, one may complete this example for when firms do not innovate for two consecutive periods.}

2.4 Investment Strategies

I consider two types of RJVs. One is RJV cartelization (CJ) where firms share a single probability of research
success and choose investment to maximize the discounted sum of joint profits.\footnote{In RJV cartelization perfect monitoring is assumed so that firms do not deviate from research collusion.} The other type is RJV
competition (NJ) where firms share the single probability of research success but maximize the discounted
sum of individual profits.

In an RJV cartel the firms solve

\[
\max_{x_1, x_2} (V_1 + V_2),
\]
where \( V_j \) is defined in equation (5). Given that firms remain cooperative, research expenditures are determined by

\[
1 = \beta a_1 \left( 1 + \sigma a_2 x_C^J \right) (1 - f^J)^2 \left( (EV_{1}^s - EV_{1}^n) + (EV_{2}^s - EV_{2}^n) \right),
\]

\[
1 = \beta a_2 \left( 1 + \sigma a_1 x_C^J \right) (1 - f^J)^2 \left( (EV_{1}^s - EV_{1}^n) + (EV_{2}^s - EV_{2}^n) \right).
\]

Solving these conditions implies that each firm’s contribution to an RJV is

\[
x_C^J = x_C^J + \frac{1}{\sigma} \left( \frac{1}{a_1} - \frac{1}{a_2} \right).
\]

(6)

It means that a firm whose research efficiency, \( a_i \), is higher should invest more by \( \frac{1}{\sigma} \left( \frac{1}{a_j} - \frac{1}{a_i} \right) \). Interestingly the contribution does not depend on the expected return. When member firms are equally efficient in their research, they spend equally even if their gains are different.

When there is no spillover (\( \sigma = 1 \)), research expenditures can be solved as

\[
x_C^J = \max \left\{ \left( \frac{\beta \left( EV_{1}^s - EV_{1}^n + EV_{2}^s - EV_{2}^n \right)}{a_1 a_2} \right)^{\frac{1}{2}} - \frac{1}{a_1}, 0 \right\}
\]

\[
x_C^J = \max \left\{ \left( \frac{\beta \left( EV_{1}^s - EV_{1}^n + EV_{2}^s - EV_{2}^n \right)}{a_1 a_2} \right)^{\frac{1}{2}} - \frac{1}{a_2}, 0 \right\}.
\]

(7)

It shows that research expenditure is a function of the sum of the net expected returns.

In RJV competition research expenditure is determined by

\[
1 = \beta a_1 \left( 1 + \sigma a_2 x_C^N \right) (1 - f^J)^2 \left( EV_{1}^s - EV_{1}^n \right),
\]

\[
1 = \beta a_2 \left( 1 + \sigma a_1 x_C^N \right) (1 - f^J)^2 \left( EV_{2}^s - EV_{2}^n \right),
\]

given that firms remain cooperative. The contribution rule in this regime is

\[
x_C^N = \frac{1}{\sigma} \left( \frac{1}{a_1} \left( EV_{2}^s - EV_{2}^n \right) - \frac{1}{a_2} \right) + \left( EV_{2}^s - EV_{2}^n \right) x_C^N.
\]

(7)

12
The contribution depends on the relative gains from research success, i.e., \( \frac{(EV_s^r - EV_n^r)}{(EV_s^l - EV_n^l)} \), such that a firm whose expected gain is higher contributes more to an RJV even when the efficiency level is the same.

As in an RJV cartel, research expenditure can be analytically expressed when there is no spillover. The resulting expressions are:

\[
x_{1J}^N = \begin{cases} 
\max \left\{ \left( \frac{\beta (EV_s^r - EV_n^r)^2}{a_1a_2(\bar{EV}_1^r - \bar{EV}_2^r)} \right)^{\frac{1}{3}} - \frac{1}{a_1}, 0 \right\}, & \text{if } (EV_s^r - EV_n^r) > 0, \\
0, & \text{otherwise}
\end{cases}
\]

\[
x_{2J}^N = \begin{cases} 
\max \left\{ \left( \frac{\beta (EV_s^r - EV_n^r)^2}{a_1a_2(\bar{EV}_1^r - \bar{EV}_2^r)} \right)^{\frac{1}{3}} - \frac{1}{a_2}, 0 \right\}, & \text{if } (EV_s^r - EV_n^r) > 0, \\
0, & \text{otherwise}
\end{cases}
\]

In contrast to RJV cartelization, a firm’s research expenditure is negatively affected by the other firm’s expected gain.

When firms unilaterally invest without forming an RJV \((N)\), firm \(j\)'s research expenditure, given firm \(k\)'s research expenditure, satisfies

\[1 = \beta a_j \left(1 + \sigma a_k x_k^N \right) \left(1 - f_j \left(\cdot\right)\right)^2 \left(\bar{EV}_j^s - \bar{EV}_j^n\right),\]

where \(f_j\) is defined in equation (1). When there is no spillover, firm \(j\)'s research expenditure is simplified to

\[x_j^N = \max \left\{ \left( \frac{\beta (\bar{EV}_j^s - \bar{EV}_j^n)}{a_j} \right)^{\frac{1}{2}} - \frac{1}{a_j}, 0 \right\},\]

which is identical to the investment policy function in Pakes and McGuire (1994).

### 2.5 Consumer Demand and Product Market Competition

I assume that potential consumers make two-stage decisions. In the first stage they decide whether to “participate” in the market and in the second stage, if they decided to participate, they decide which processor to buy. The first stage decision determines the size of total demand and the second stage decision determines the firms’ (within) market shares. The unconditional probability of purchasing product \(j\) is
the product of the participation probability and the probability of purchasing product \( j \) conditional on participation. That is,

\[
\text{Pr}(\text{purchase } j) = \text{Pr}(\text{participate}) \times \text{Pr}(\text{purchase } j|\text{participate})
\]

Note that \( \text{Pr}(\text{purchase } j|\text{not participate}) = 0 \).

Let the sale of product \( j \) be \( Q_j \) and the number of potential consumers, or equivalently the market size, be \( M \). Then

\[
\text{Pr}(\text{purchase } j) = \frac{Q_j}{M} \quad \text{and} \quad \text{Pr}(\text{participate}) = \frac{\sum_{j=1}^{J} Q_j}{M}
\]

Therefore,

\[
\text{Pr}(\text{purchase } j|\text{participate}) = \frac{Q_j}{\sum_{j=1}^{J} Q_j}
\]

which is the within-market share of product \( j \).

I assume that consumer utility conditional on market participation is defined as

\[
u_{ij} = \delta_j - \alpha p_j + \epsilon_{ij}, \quad \text{for } j = 1, 2, \ldots, J
\]

\[
u_{i0} = \epsilon_{i0}
\]

where \( \delta_j \) denotes product \( j \)'s quality, \( p_j \) its price with the coefficient \( \alpha \), and \( \epsilon_{ij} \) is i.i.d. Type I extreme value, a.k.a., an idiosyncratic logit error term. \( u_{i0} \) is the utility of an outside option and I normalize its mean value to zero. The outside option is to choose products that I do not have data on.

Because of the distributional assumption on \( \epsilon_{ij} \),

\[
\text{Pr}(\text{purchase } j|\text{participate}) = \frac{\exp(\delta_j - \alpha p_j)}{1 + \sum_{k=1}^{J} \exp(\delta_k - \alpha p_k)}
\]

Thus, I can estimate consumer preference by linking within-market shares to product characteristics and
prices. Let $s_j$ be product $j$’s within-market share and $s_0$ be the outside option’s share. Assuming that product quality linearly depends on product characteristics, the demand equation is

$$\ln (s_j) - \ln (s_0) = x_j \beta - \alpha p_j + \xi_j$$

where $x_j$ includes product characteristics such as the processing speed, the capacity of the level two cache (L2 cache), and the time dummy variables. $\xi_j$ represents the unobserved quality.

An underlying assumption in the demand model is that the participation probability is not a function of quality and price of products currently being sold in the market. It is not an innocuous assumption. Some consumers may not participate in the market because they are waiting for prices to fall or for new products to come out. To describe these consumers one needs a dynamic demand model that includes the option value of waiting as a function of not only the current period product quality and prices but also the consumer’s expectations of future product quality and future prices. Although a dynamic demand model is more realistic, making both firms and consumers forward-looking agents is beyond the scope of this paper. Nevertheless, as explained in section 2.3, I still make the participation decision relevant for firms’ investment decision via the use of total demand fluctuation as a state variable.

Firms compete à la Bertrand in the product market. So given the product quality of all products in the market, $\delta$, and the unit cost of production $c_j$, a firm sets a price $p_j$ to maximize

$$\pi_j = (p_j - c_j) Q_j (p)$$

where $Q_j (p)$ denotes the quantity of product $j$ sold. With the demand model described above profit always increases as product quality improves. This condition is necessary to obtain Markov Perfect Equilibrium in the dynamic model.

When firms succeed in developing a new technology, they are able to improve product characteristics. In the case of the CPU, when SEMATECH succeeds in advancing photolithography technology, Intel

---

12 The participation probability is equivalent to a time varying constant added onto demand.

and AMD are able to increase their processing speeds. The coefficient on the processing speed quantifies consumers’ willingness to pay for a faster CPU and determines how much a firm’s profit increases from successful research.

While firms cooperate in developing the generic technology, they also compete to develop better products. The whole process of product development may consist of many stages and involve technologies that are unilaterally developed by each firm. Instead of modeling this process, I use the unobserved quality, \( \xi \), to estimate the product quality determined by unilateral product development.

Lastly, I assume that firms are not allowed to appropriate the other firm’s research outcome when they do not cooperate. Therefore, in the competitive research regime, a firm can only increase the maximum processing speed via its own research success.\(^{14}\) However, this assumption is irrelevant to RJVs where the maximum processing speed is always the same for both firms and their product market competitiveness is solely determined by the unobserved quality.

\section{SEMATECH}

In August of 1987 SEMATECH was incorporated with thirteen U.S. charter members. U.S. producers had dominated the world semiconductor market in the 1970s, but were facing an increasing challenge from Japanese counterparts in the late 1970s. By the mid-1980s, their market share had dropped significantly, and both the industry and the Department of Defence proposed the creation of an RJV.

SEMATECH started with an initial budget of 250 million dollars in 1988 with the federal government and the member firms each contributing 100 million dollars. The remaining funds were provided by state and local funds from Austin, Texas, where SEMATECH was (and still is) located. The government reduced its funding gradually over time, and stopped it entirely in 1998 when the SEMATECH board determined that federal funding was no longer needed. As of 2005 its 170 million dollar annual budget was mainly funded by member dues. Other sources include funding from the states of Texas and New York for selected programs and royalties. Data on the individual members’ contributions to SEMATECH are not publicly available. However, it is known that before the federal government stopped its funding, members were

\(^{14}\) An alternative assumption would be that a firm can adopt other firms’ research outcomes by paying a licensing fee.
required to contribute one percent of their semiconductor sales revenue, with a minimum of 1 million dollar
and a maximum of 15 million dollars (Irwin and Klenow, 1996b).

This contribution rule suggests that SEMATECH has features of both RJV cartelization and RJV
competition. The contribution based on sales revenue is similar to the contribution rule in RJV competition;
however, the upper bound is similar to the contribution rule in RJV cartelization. The bounds ensure that
the contribution is not too drastically different among members.

SEMATECH's members have changed over time. The initial thirteen members were all U.S. pro-
ducers, and they were Advanced Micro Devices (AMD), AT&T, Digital Equipment Corp., Harris Corp.,
National Semiconductor Corp., Rockwell International Corp., and Texas Instruments Inc. Some members
like LSI Logit and Micron Technology left SEMATECH when they concluded they would not benefit from
a joint investment. In 2000 SEMATECH abandoned its original intent to keep the consortium limited to
U.S. companies and became International SEMATECH. As of 2005 the U.S. members are AMD, Freescale
Semiconductor, Hewlett Packard, IBM, Intel, Spansion, and Texas Instruments. The non-U.S. members
are Infineon Technologies (Germany), NEC (Japan), Panasonic (Japan), Philips (Netherlands), Renesas
Technology (Japan), Samsung (South Korea), and TSMC (Taiwan).

Out of the fourteen members only Intel, AMD, and IBM produce CPUs for personal computers. Dur-
ing the sample period (from 1993 to 2000) IBM exclusively supplied CPUs to Apple Computer and its market
share was about 2 percent.\textsuperscript{15} Because of data availability and its non-compatibility with other brand PCs I
exclude IBM from the analysis. The other members mainly produce memory chips and microcontrollers.\textsuperscript{16}

SEMATECH's goal has changed over time. When it was first incorporated, SEMATECH decided
to pursue the development of an end-to-end manufacturing process and, to this end, built a large-scale
fabrication facility in Austin. However, it had difficulty developing a research agenda that would satisfy all
members as they had different technological advantages and were reluctant to share them.

In 1991, SEMATECH switched its goal to developing and qualifying equipment for new photolitho-

\textsuperscript{15}In June, 2005, Apple Computer announced that it would switch its computers to Intel's microprocessors as early as 2006.
\textsuperscript{16}The microcontroller is used to control electronic devices like washing machines, microwave ovens, telephones etc.
graphy technology. The wavelength of ultraviolet light used in this technology determines the maximum number of transistors inscribed on the silicon wafer. With more transistors the semiconductor can store more information and/or execute more complicated instructions. This technology is generic rather than product-specific or firm-specific. Table 1 shows generations of the CPU associated with the advancement of photolithography technology.

4 Results

My analysis consists of two stages. In the first stage, I use product level data to estimate the demand side parameters and the transition probabilities of the unobserved quality. In the second stage, research expenditure and firm value are computed as a solution to the dynamic model. The computation algorithm is a modification of the algorithm in Pakes and McGuire (1995). The main difference is that in RJVs firms share a transition probability of research success which is a function of both firms’ research expenditures. I do not consider entry decisions. There was no new entrant in the CPU market during the sample period, which suggests that the entry cost is too high for any potential entrants.

4.1 Demand Estimates

For demand estimation I use quarterly data on price, units sold, and the product characteristics of Intel and AMD products. Price and quantity data are from MicroDesign Resources (MDR), an independent research group that collects data on the CPU market. The sample period starts at the second quarter of 1993 and ends in the third quarter of 2000. Intel and AMD are two major producers during the sample period with the combined market share of over 90 percent. I treat 386 and 486 class processors as the outside option because price data on these products are not available.

Data being quarterly is not in conflict with the time interval in the dynamic model. The demand parameters represent consumers’ marginal utility with respect to product attributes. They are not time-related parameters and higher frequency data are used to consistently estimate them. However, estimates of the unobserved quality are sensitive to quarterly data. Quantitative results may change with different

\(^{17}\) For the evolution of SEMATECH objectives, see Grindley, Mowery, and Silverman (1994).
frequency data. However, as long as they consistently reflect firms’ relative competitiveness, the qualitative results should not change.

I treat each quarter in the world CPU market as a different market. Therefore, my sample consists of 30 markets and 320 observations. As explained in section 2.5, a (within) market share is defined as the number of units sold divided by the total number of CPUs sold. The outside option is to buy CPUs produced by firms other than Intel and AMD such as the IBM CPUs used in Apple computers. Summary statistics are provided in table 2 and more details on the data can be found in Song (2007).

The observable characteristics are \( \log(\text{Speed}) \), \( \log(\text{Speed}) \) squared, and a dummy variable for having different capacities of the level-2 cache (\text{No\_Cache}). By using the log of the processing speed, I restrict product quality to be a monotonically increasing function of the processing speed. I also include the time dummy variables which capture quarterly changes in the mean value of the unobserved quality and quarterly changes in the value of the outside option. However, without additional assumptions only the sum of these effects is identified. I do not attempt to separate these two effects as it is irrelevant to my analysis.\(^{18}\)

The demand equation (equation (8)) is estimated using the GMM with moment conditions that the product characteristics excluding price are not correlated with the detrended unobserved quality. Price is an endogenous variable that can be correlated with the unobserved quality. In particular, I use the log of the processing speed interacted with the time dummy variables as instruments. They are used as proxies for the production cost. In this industry the processing speed increases over time, but the production cost does not change much. By interacting the processing speed with the time dummy variables I reflect the stability of the production cost over time.

Demand estimates are reported in table 3. The first two columns report estimates without using the instruments. With the instruments the price coefficient goes down while all other coefficients hardly change (the third and the fourth columns). The standard errors of all the coefficients go up with the instruments, but the coefficient on the log of the processing speed is still statistically significant. The coefficients on product characteristics measure the consumers’ willingness to pay for an improvement in the corresponding characteristic. The coefficient on the processing speed in particular determines firms’ profitability from

\(^{18}\)The two time effects are separated in the pure characteristics demand model in Song (2007).
research success. According to the estimates in the third column the consumer is willing to pay 400 to 450 dollars for a 100MHz increase in the processing speed when she has a 300 MHz processor, and 200 to 230 dollars when she has a 600 MHz processor. With the log of the processing speed squared added (the fourth column), the consumer is willing to pay 410 to 480 dollars when she has a 300 MHz processor, and 220 to 270 dollars when she has a 600 MHz processor.

I use the estimates in the third column (IV logit 1) in the dynamic model. Although the IV logit model is no better than the logit model in terms of statistical significance, the estimate on the price coefficient is more reasonable. That being said, the key results are not sensitive to which estimates are used. The estimates on the unobserved quality are very similar across the specifications. Comparing the logit and the IV logit models, the mean difference is 0.033 with the standard deviation 0.021 for Intel and -0.003 with the standard deviation 0.014 for AMD.

4.2 State Variables and Transition Probabilities

I choose five levels of the processing speed to trace the advancement of the photolithography technology, and they are 66, 200, 333, 800, and 1000 MHz. They match the maximum processing speed in 1993, 1995, 1997, 1999, and 2000 respectively. Then I add 1500, 2100, and 2800 MHz to ensure that firms still have an incentive to invest when the maximum speed approaches 1,000 MHz.

The transition probability of the maximum speed is represented by the probability of research success. That is, for firm $j$,

$$q_j (\text{Speed}_{t+1}|\text{Speed}_t, \omega_t) = f^J (x_t | a, \sigma, \omega_t)$$

in RJVs where $f^J (x_t | a, \sigma, \omega_t)$ is defined in equation (3) and

$$q_j (\text{Speed}_{t+1}|\text{Speed}_t, \omega_t) = f_j (x_t | a, \sigma, \omega_t)$$

in competitive research where $f_j (x_t | a, \sigma, \omega_t)$ is defined in equation (1). The transition probabilities are determined by the firms’ research expenditures in a Markov perfect equilibrium.

A detrended value of the unobserved quality captures product quality that is unrelated to the process-
ing speed and is estimated by
\[ \hat{\xi} = \delta - x\hat{\beta} \]

where \( x \) contains the observed characteristics including the time dummy variables, and \( \hat{\beta} \) is the estimated coefficient. For Intel I take the average value of the three most expensive products’ unobserved quality. For AMD I take the most expensive product group’s unobserved quality as its data are more aggregated. This selection is consistent with the assumption that firms produce one frontier product each.

Figure 1 shows the trends in the unobserved quality of Intel’s and AMD’s frontier products. The figure shows an important change in the CPU market in the late 1990’s. Before the late 1990s Intel’s unobserved quality increases steadily and is better than that of AMD’s. However, in the late 1990s AMD’s unobserved quality, which was volatile previously, becomes steady and improves rapidly, while Intel shows no sign of improvement. I explore the effect of this change on research expenditure in section 6.

I follow Tauchen (1986) in estimating the transition probability of the unobserved quality. I estimate an AR(1) process and follow Tauchen’s procedure to discretize a grid and estimate the first order stochastic process \( \eta (\xi_{t+1} | \xi_t) \). Table 4 reports the discretization grid and the transition probabilities. The remaining model parameters are the investment efficiency, \( a_j \), the degree of spillover, \( \sigma \), the discount rate, \( \beta \), and the unit cost, \( c_j \). The investment efficiency and the degree of spillover are set to 1 and the discount rate is set to 0.98.\(^{19}\) The unit cost is set to the overall quality \( \delta_j \) divided by 10. The sensitivity of research expenditure to different values is reported in section 4.3.

### 4.3 Research Expenditure

I first compute the firms’ static profits for every combination of the state variables. Then, given static profits, transition probabilities of the unobserved quality, and other parameters of the model, I solve the dynamic model to obtain research expenditure. I let the market size increase at a constant rate (10\%) whenever the maximum speed improves to the next level. This is equivalent to adding new potential consumers into market whenever there is a technological innovation. This partially offsets the diminishing return to research expenditure.

\(^{19}\) Alternatively, Besanko and Doraszelski (2004) set \( a \) such that \( f (\pi | a) = \overline{\pi} \) where \( \pi = 20 \) and \( \overline{\pi} = 0.5. \)
Table 5 shows the mean and the standard deviation of research expenditures at various levels of the maximum processing speed. The standard deviation shows that research expenditure varies considerably depending on where firms are in the state space. Most of the variation is due to whether there was an innovation in the last period. Because of the endogenous demand fluctuation, firms have much stronger incentives to innovate after a period of no innovation. Specifically, in the RJV regimes firms spend 10 to 70 percent more after no innovation, and in the competitive research regime firms spend 20 to 65 percent more.

Firms invest equally in RJV cartelization as long as their research efficiencies are the same. In RJV competition, research expenditure depends on how much firms gain from research success. For example, when the maximum processing speed is 333 MHz, Intel spends $36.47$ million dollars and AMD spends $17.09$ million dollars in RJV competition, while they each spend $32.49$ million dollars in RJV cartelization. Therefore, Intel bears about 68 percent of research expenditure in RJV competition, but bears only 50 percent in RJV cartelization. A higher maximum speed first increases research expenditure and then reduces it. This implies that research benefit is an S-shaped function of the processor speed. An increase in the market size offsets the diminishing return but only partially.

Table 5 also shows that firms invest much more aggressively in the competitive research regime as, compared to the RJV competition regime, Intel spends about two times more and AMD over three times more. Thus, firms significantly save on research expenditure by forming an RJV. However, in the RJV regime they give up the opportunity to become a solo innovator as they fully share all research outcomes. Higher research expenditure means a higher success probability at the industry level. Thus, new technologies are more frequently introduced in a competitive research environment, and this benefits consumers. However, consumers pay higher prices for new products if only one firm succeeds in research. In the next section I simulate the industry for the three different regimes over 30 periods in order to compare firms’ profits and consumer surplus across the regimes.

Research expenditure obviously changes as the parameter values change. Consider the degree of spillover ($\sigma$) and the research efficiency ($a$), two parameters in the success probability function (see equations (1) and (2)). The degree of spillover indicates how strongly the two firms’ research outcomes are correlated when they unilaterally invest in research. In the RJV regimes, for a given research expenditure,
the probability of success increases with the degree of spillover. Thus, holding the benefit of research success
constant, research expenditure is decreasing in the spillover effect. For example, when the degree of spillover
increases from 1 to 1.5 at the maximum processing speed of 333 MHz, the average research expenditure
decreases by 11.93 percent in RJV cartelization and by 12 percent and 11.34 percent for Intel and AMD
respectively in RJV competition. In addition, as the level of spillover increases this response becomes more
muted. For example, when the degree of spillover increases from 1.5 to 2, research expenditure decreases
by 8.73 percent in RJV cartelization and by 8.77 percent and 8.39 percent for Intel and AMD respectively
in RJV competition. And when the spillover degree increases from 2 to 2.5, it decreases by 6.89 percent in
RJV cartelization and by 6.91 percent for Intel and 6.67 percent for AMD in RJV competition.

A firm’s level of research efficiency indicates the rate at which the firm is able to transform one dollar
of research expenditure into an increased probability of research success. Thus, a higher research efficiency
means that a firm can achieve the same likelihood of success with less research expenditures. Moreover, since
firms share the success probability, an increase in any firm’s research efficiency reduces both firms’ research
expenditures. For example, when the research efficiency goes up from 1 to 1.5 for Intel at the maximum
processing speed of 333 MHz, the average research expenditure decreases by 11.91 percent for Intel and 13.11
percent for AMD in RJV cartelization and by 11.96 percent for Intel and 13.48 percent for AMD in RJV
competition. When the efficiency goes up from 1 to 1.5 for AMD at the same maximum processing speed,
the expenditure decreases by 13.11 percent for Intel and 11.91 percent for AMD in RJV cartelization and
by 13.08 percent for Intel and 11.31 percent for AMD in RJV competition.

The research expenditure is also affected by a demand shock, which makes the quality of Intel and
AMD products go down at the same time. When there is a negative shock, firms tend to invest more in
the RJV regimes. For example, when the probability of having a negative shock goes up from 0.1 to 0.3 at
the maximum processing speed of 333 MHz, the average research expenditure increases by 9.87 percent in
RJV cartelization and by 10.84 percent for Intel and 8.97 percent for AMD in RJV competition. It increases
more rapidly as the probability becomes higher. At the same processing speed it increases by 17.19 percent
in RJV cartelization when the probability goes up from 0.5 to 0.7, while it increases by 29.7 percent when
the probability goes up from 0.7 to 0.9. The increasing research expenditure is due to the expected gain
from research success increasing. The expected gain is a function of the difference between firm values at two adjacent maximum speed levels. As the probability of having a shock goes up, the firm value tends to decrease at all maximum speed levels, but it decreases more at lower levels. As a result, the expected gain increases, and so does the expenditure.

My dynamic model is a limited description of SEMATECH and I do not expect the computed research expenditure to be a close estimate of what it actually spends for photolithography technology.\(^{20}\) Nevertheless, I compare the computed expenditure to the total contribution of all member firms to SEMATECH. Unfortunately, data on individual member firms’ contribution to SEMATECH are not publicly available. What is known is that member firms are responsible for 100 million dollars out of SEMATECH’s 170 million dollar annual budget. The number of members has been around 10 ~ 12, which means that each member pays around 8 to 10 million dollars if they pay equally. The computed research expenditures are somewhat higher than the actual average contributions. This gap is increased if one considers the fact that I only account for the expected return in one sector of the industry. However, one should note that each maximum speed level represents technologies introduced about every two years. Thus, it is more reasonable to interpret the computed research expenditures as the expenditure needed to introduce the next generation technology rather than the contribution to a yearly budget.

5 Welfare Analysis

I simulate the CPU market for 30 periods for each research regime to compare the discounted sum of net profit and consumer surplus. The starting point is a state where both firms produce a 200 MHz CPU, the unobserved qualities are −0.538 and −2.800 respectively, total demand is at a low level and there was no innovation in the previous period. I iterate the simulation 5,000 times to account for four types of random outcomes. The first is whether firms succeed in research or not. The second is whether there is a negative demand shock, for which I set the probability to 0.7. The third and fourth outcomes related to how the two firms’ unobserved qualities evolve over time (according to the probabilities reported in table 4). For the model parameters I use the default values. I cover almost all patterns of the industry evolution by simulating

\(^{20}\)I will discuss limitations in more details in section 7.
for 30 periods and repeating 5,000 times. The probability that the maximum processing speed reaches 2.8 GHz is about 0.5 after 20 periods for all research regimes, and is over 0.90 at the 30th period.

In table 6 I compare the discounted sum of net profit and consumer surplus for a pair of regimes. The table describes the distributions of their differences by reporting the mean, standard deviation, skewness, and kurtosis. The mean is equivalent to the expected value and the other statistics describe shapes of the difference distributions. In each iteration the two regimes being compared share all random outcomes except for research success. Therefore, the differences are driven by different paths of the technological evolution across the regimes.

The first column of table 6 compares RJV competition (NJ) with competitive research (N). It shows that the expected net profits are higher for both Intel and AMD in RJV competition. Profit is 46.7 million dollars higher for Intel and 97.5 million dollars higher for AMD. Higher expected net profit in RJV competition means that the cost savings outweigh the foregone benefit of being a solo innovator. The distribution of net profit differences is left-skewed, and the standard deviation and kurtosis show that it has a much sharper peak and longer and fatter tails than the normal distribution. This shape implies that firms can still earn higher net profits from solo innovations in competitive research but it does not happen frequently enough to dominate the cost saving benefit.

The expected consumer surplus is also higher in RJV competition. Firms introduce new products more frequently in competitive research, but consumers will be forced to pay higher prices for the same quality products in RJV competition. The net effect is that the benefit of paying lower prices in RJV competition outweighs that of having new products more frequently in competitive research. This distribution is also left-skewed and has a sharper peak with longer and fatter tails than the normal distribution.

The comparison between RJV cartelization (CJ) and competitive research (N) (in the second column) is qualitatively similar. RJV cartelization leads to larger consumer surplus and higher expected net profits for both Intel and AMD. The shape of the difference distributions is almost identical.

The last column of table 6 compares RJV cartelization and RJV competition. Compared to the previous two comparisons, Intel’s expected net profit is not much different between the two regimes, although it is higher in RJV cartelization. On the other hand, AMD’s expected net profit is higher in RJV competition.
by about 24 million dollars. This is because Intel tends to spend less in RJV cartelization, while AMD tends
to spend less in RJV competition. This suggests that Intel, a dominant firm, prefers RJV cartelization, while
AMD prefers RJV competition. It also raises the question of what type of RJV the two firms would agree
to have. The answer will depend on who has more bargaining power and how they negotiate. In any case
firms are unlikely to compete in research since both types of RJV dominate competitive research.\textsuperscript{21}

The expected consumer surplus is about 14 million dollars higher in RJV cartelization. This is
because the research success probability is slightly higher in RJV cartelization. Note that consumers pay
the same price for the same quality product in both regimes. Nevertheless, total welfare is the largest in
RJV competition as AMD’s expected net profit is much higher.

6 Product Market Competition and Cooperative Research

In this section I ask how changes in the market structure affect research behavior. In particular, I look at
how research expenditure changes as the product market becomes more competitive. The relation between
market structure and innovation has been debated theoretically and empirically since Schumpeter (1942),
but has never been analyzed in the context of research cooperation.

This question is relevant to the CPU market during the sample period. The market became more
competitive in the late 1990s as AMD’s frontier products, the K6 and K6-2 processors, were successful at
the high end of the market. Intel lost about 14 percent of the total market share from the third quarter
of 1997 to the fourth quarter of 1998. In my model the unobserved quality indicates this change. Figure 1
shows that in the late 1990s AMD’s unobserved quality steadily improved, while Intel’s did not. As a result,
the quality gap between the two rivals became narrower.

The unobserved quality is an ideal variable to use in the counterfactual exercise since it is an ex-
genous variable that it is not affected by innovation outcomes. I manipulate its transition probability and
compute research expenditure in a new equilibrium. In particular, I replace AMD’s unobserved quality
and transition probability with those of Intel, so the two firms produce the exact same products in the

\textsuperscript{21}It is interesting that SEMATECH has features of both types of RJV as discussed in section 3. The member contribution
is based on sales revenue but has the lower and upper bounds. AMD is likely to benefit from the former feature, and Intel is
likely to benefit from the latter.
counterfactual setting.22

Given the same research outcomes, AMD should be better off in the counterfactual setting due to increased product quality. Intel, on the other hand, should be worse off as it loses its competitive edge. If they invest competitively, the two firms’ research expenditures are expected to move in the opposite direction. AMD would invest more aggressively because its reward from innovation is bigger, and Intel less aggressively for the opposite reason.

In RJV cartelization, however, the total research expenditure is determined by the sum of the expected benefit, so a result depends on whether Intel’s loss is bigger than AMD’s gain. In RJV competition research expenditure depends on a relative gain; therefore, firms may change it in the same direction as in the competitive research regime. However, as shown in equation (7), expenditure is likely to be more sensitive to a rival’s gain.

Table 7 compares the expected discounted sum of research expenditure over 30 periods. The simulation is repeated 5,000 times to account for the random events. The simulation shows that the expected research expenditure decreases for both firms in RJV cartelization in the more competitive market. This means that the total expected profit is lower in the more competitive market, although the magnitude is not significant. In RJV competition AMD’s research expenditure goes up by 41 percent, while Intel’s goes down by 32 percent. This confirms that the two firms have the opposite investment incentives. The total expenditure is lower because AMD’s increased expenditure does not offset Intel’s decreased expenditure. However, as expected, these changes are more significant than in the competitive research regime where AMD’s research expenditure only goes up by 19 percent, and Intel’s only drops 16 percent.

This result sheds light on a cause of the accelerated technological change in the semiconductor industry. There is a consensus that the product cycle was reduced from three years to two years beginning in 1995.23 Jorgenson (2001) associates this change with increased productivity growth in the U.S. economy, but points out that there is not a fully satisfactory economic model that explains this change.24 One hypothesis I can test is that more intense competition in the product market caused SEMATECH to accelerate

---

22 An alternative exercise is to divide the sample period into two eras and estimate the transition probability separately. However, the sample size is not large enough for this method.


24 Azicorbe and Kortum (2005) use a vintage model to explain the link between technological improvements and price declines of individual products. However, technological improvement is given exogenously in their model.
technological change.

My results do not support this hypothesis. Instead, they predict that the technological change slows down if SEMATECH members foresee a more competitive product market. The average probability of research success goes down in the RJV regimes because of reduced research expenditure. In RJV cartelization the probability of research success is lower in 80 percent of 5,000 iterations. In RJV competition the probability is lower in 67 percent.

7 Conclusions and Discussions

In this paper I construct a dynamic model of RJVs in which firms competing in the product market cooperate to improve product quality. Research success is a stochastic event and the probability of research success is a function of the firms’ research expenditures. I model cooperative research by making the firms share the probability of research success.

The model presents trade-offs that both firms and consumers face with RJVs. Firms may benefit from RJVs because they can eliminate duplicative research efforts, but they must give up the possibility of becoming a solo innovator. Consumers may benefit from RJVs with lower prices since the rent from innovation is shared by all member firms, but may wait longer for a new product to arrive.

Using the dynamic model and the demand parameters estimated with the CPU market data, I show that RJVs are welfare enhancing. RJVs reduce research expenditure by twenty five to fifty percent when compared to a competitive research regime. These cost savings outweigh the expected gain of becoming a solo innovator. Intel's net profit is about 50 million dollars higher over 30 periods, while AMD’s is about 100 million dollars higher. Consumer surplus is also higher by about 200 million dollars, demonstrating that the benefit of lower prices outweighs that of more frequent new product introductions.

I also show that more intense product market competition may slow down the speed of innovation. A laggard firm has an incentive to invest more aggressively in a more competitive market, but a dominant firm has the opposite incentive. Given the functional form and estimated parameter values, the total research expenditure decreases in both RJV regimes as the laggard firm’s gain is no larger than the dominant firm's loss.
One should note that I only analyze one aspect of research cooperation in this paper. There are at least two other important aspects that are excluded from my analysis. One is research cooperation for the process innovation and the other is the interaction among multiple RJVs in the same industry. Both aspects are present in the semiconductor industry. SEMATECH coordinates the process innovation by setting up a standard wafer size and determining when to move up to a larger size. The wafer is the basic unit of production, on which identical semiconductors are made. Since identical chips are produced from a given size of the wafer, a larger size means a lower unit cost. In the mid 1990s, SEMATECH began leading an international conversion from eight-inch diameter wafers to twelve-inch diameter wafers.

My model can be easily modified to incorporate the process innovation, and adding it may make the model more realistic. However, it complicates the analysis without changing the main results. Both types of innovation benefit firms by increasing their expected profits, but the product innovation is a "drastic" innovation that has a larger impact.

The interaction among multiple RJVs is an interesting aspect of RJVs but it is beyond the scope of this paper. It is still important in the semiconductor industry. SEMATECH was formed as a counterpart to other RJVs in Japan and Europe and started to seek areas of possible cooperation with them as early as 1989. The memory chip sector is an interesting industry for studying this aspect as firms belong to different RJVs such as SEMATECH and SELETE, a Japanese RJV.
References


<table>
<thead>
<tr>
<th>Year</th>
<th>Type</th>
<th># of transistors (in thousands)</th>
<th>Technology(^\d)</th>
<th>Photolithography system</th>
</tr>
</thead>
<tbody>
<tr>
<td>1971</td>
<td>4004</td>
<td>2.3</td>
<td>10</td>
<td>contact aligners</td>
</tr>
<tr>
<td>1972</td>
<td>8008</td>
<td>3.5</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>1974</td>
<td>8080</td>
<td>6</td>
<td>6</td>
<td>proximity aligners</td>
</tr>
<tr>
<td>1979</td>
<td>8088</td>
<td>29</td>
<td>3</td>
<td>projection aligners</td>
</tr>
<tr>
<td>1982</td>
<td>286</td>
<td>134</td>
<td>1.5</td>
<td>first G-line steppers</td>
</tr>
<tr>
<td>1985</td>
<td>386DX</td>
<td>275</td>
<td>1</td>
<td>advanced G-line steppers</td>
</tr>
<tr>
<td>1989</td>
<td>486DX</td>
<td>1200</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>Pentium</td>
<td>3100</td>
<td>0.8</td>
<td>first I-line steppers</td>
</tr>
<tr>
<td>1995</td>
<td>Pentium Pro</td>
<td>5500</td>
<td>0.35</td>
<td>advanced I-line steppers</td>
</tr>
<tr>
<td>1997</td>
<td>Pentium II</td>
<td>7500</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>Pentium III</td>
<td>28000</td>
<td>0.18</td>
<td>first deep-UV steppers</td>
</tr>
<tr>
<td>2000</td>
<td>Pentium IV</td>
<td>42000</td>
<td>0.18</td>
<td></td>
</tr>
</tbody>
</table>


\(^\d\)The number indicates the wavelength of ultraviolet light used in the photolithography technology. A smaller wavelength allows more transistors to be inscribed on the processor.
Table 2: Summary Statistics: CPUs from 1993Q2 to 2000Q3

<table>
<thead>
<tr>
<th>Year</th>
<th>Speed (in MHz)</th>
<th>Price (in dollar)</th>
<th>Share†</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
<td>Max</td>
</tr>
<tr>
<td>1993</td>
<td>60</td>
<td>63</td>
<td>66</td>
</tr>
<tr>
<td>1994</td>
<td>60</td>
<td>79.7</td>
<td>100</td>
</tr>
<tr>
<td>1995</td>
<td>60</td>
<td>102</td>
<td>200</td>
</tr>
<tr>
<td>1996</td>
<td>75</td>
<td>143.2</td>
<td>200</td>
</tr>
<tr>
<td>1997</td>
<td>90</td>
<td>189.6</td>
<td>333</td>
</tr>
<tr>
<td>1998</td>
<td>166</td>
<td>290.4</td>
<td>450</td>
</tr>
<tr>
<td>1999</td>
<td>300</td>
<td>467.1</td>
<td>800</td>
</tr>
<tr>
<td>2000</td>
<td>433</td>
<td>615.6</td>
<td>1000</td>
</tr>
</tbody>
</table>

†The mean price is the average price weighted by quantity.
†Share is defined as quantity sold divided by the total number of products sold in the market.
Table 3: Estimates of consumer demand in the CPU market

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Logit 1</th>
<th>Logit 2</th>
<th>IV Logit 1</th>
<th>IV Logit 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.83** (0.75)</td>
<td>-2.13** (0.81)</td>
<td>-1.74 (1.36)</td>
<td>-2.08 (1.50)</td>
</tr>
<tr>
<td>log(Speed)</td>
<td>1.49** (0.43)</td>
<td>1.31** (0.46)</td>
<td>1.46* (0.87)</td>
<td>1.45* (0.87)</td>
</tr>
<tr>
<td>(log(Speed))^2</td>
<td></td>
<td></td>
<td>0.18 (0.18)</td>
<td>0.11 (0.20)</td>
</tr>
<tr>
<td>No_Cache(^{\circ})</td>
<td>-0.20 (0.21)</td>
<td>-0.17 (0.21)</td>
<td>-0.23 (0.24)</td>
<td>-0.22 (0.24)</td>
</tr>
<tr>
<td>Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>-1.09** (0.46)</td>
<td>-1.19** (0.47)</td>
<td>-1.20 (1.06)</td>
<td>-1.37 (1.10)</td>
</tr>
<tr>
<td>(N)</td>
<td>321</td>
<td>321</td>
<td>321</td>
<td>321</td>
</tr>
</tbody>
</table>

Standard errors are reported in parenthesis.
In every specification, dummy variables for quarters are included.
\(^{\circ}\)No_Cache is a dummy variable for processors with lower capacity of the level 2 cache.
*significant at the 10% level.
**significant at the 5% level.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi_{\text{Intel}}$</td>
<td>Unob. quality for Intel</td>
<td>${-1.195, -0.538, 0.120, 0.778, 1.436}$</td>
</tr>
<tr>
<td>$\eta_{\text{Intel}}(\xi_{t+1}</td>
<td>\xi_t)$</td>
<td>Transition matrix of $\xi_{\text{Intel}}$</td>
</tr>
<tr>
<td>$\xi_{\text{AMD}}$</td>
<td>Unob. quality for AMD</td>
<td>${-4.207, -2.800, -1.394, 0.013, 1.420}$</td>
</tr>
<tr>
<td>$\eta_{\text{AMD}}(\xi_{t+1}</td>
<td>\xi_t)$</td>
<td>Transition matrix of $\xi_{\text{AMD}}$</td>
</tr>
</tbody>
</table>

See the text for details.
Table 5: Average research expenditure in Markov Perfect Equilibrium (in million dollars)

<table>
<thead>
<tr>
<th>Maximum Speed</th>
<th>RJV cartelization</th>
<th>RJV competition</th>
<th>Competitive research</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intel</td>
<td>AMD</td>
<td>Intel</td>
</tr>
<tr>
<td>66 MHz</td>
<td>Mean</td>
<td>20.74</td>
<td>20.74</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>1.87</td>
<td>1.87</td>
</tr>
<tr>
<td>200 MHz</td>
<td>Mean</td>
<td>33.48</td>
<td>33.48</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>1.28</td>
<td>1.28</td>
</tr>
<tr>
<td>333 MHz</td>
<td>Mean</td>
<td>32.49</td>
<td>32.49</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>2.28</td>
<td>2.28</td>
</tr>
<tr>
<td>800 MHz</td>
<td>Mean</td>
<td>31.03</td>
<td>31.03</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>3.54</td>
<td>3.54</td>
</tr>
<tr>
<td>1,000 MHz</td>
<td>Mean</td>
<td>29.34</td>
<td>29.34</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>5.06</td>
<td>5.06</td>
</tr>
</tbody>
</table>

The degree of spillover is set to 1.
Table 6: Distributions of discounted sum of net profits and consumer surplus differences (in million dollars)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>CJ - N</th>
<th>CJ - NJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intel’s Net Profits</td>
<td>46.7</td>
<td>47.4</td>
<td>0.6</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>677.8</td>
<td>615.7</td>
<td>275.2</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.7</td>
<td>-0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>10.0</td>
<td>10.9</td>
<td>57.3</td>
</tr>
<tr>
<td>AMD’s Net Profits</td>
<td>97.5</td>
<td>73.3</td>
<td>-24.2</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>341.6</td>
<td>312.3</td>
<td>140.9</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.3</td>
<td>-0.4</td>
<td>-0.9</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>10.4</td>
<td>9.4</td>
<td>85.5</td>
</tr>
<tr>
<td>Consumer Surplus</td>
<td>205.5</td>
<td>219.5</td>
<td>14.1</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1,637.0</td>
<td>1,388.9</td>
<td>851.2</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.9</td>
<td>-0.6</td>
<td>2.4</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>17.9</td>
<td>17.7</td>
<td>68.4</td>
</tr>
</tbody>
</table>

NJ denotes RJV competition, CJ RJV cartelization, and N competitive research. The simulation is repeated for 5,000 times.
Table 7: Discounted sum of research expenditure in a more competitive market (in billion dollars)

<table>
<thead>
<tr>
<th></th>
<th>RJV cartelization</th>
<th></th>
<th>RJV competition</th>
<th></th>
<th>Competitive research</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>before after</td>
<td></td>
<td>before after</td>
<td></td>
<td>before after</td>
<td></td>
</tr>
<tr>
<td>Intel</td>
<td>0.63 0.60</td>
<td></td>
<td>0.77 0.52</td>
<td></td>
<td>2.12 1.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.07) (0.07)</td>
<td></td>
<td>(0.11) (0.07)</td>
<td></td>
<td>(0.42) (0.39)</td>
<td></td>
</tr>
<tr>
<td>AMD</td>
<td>0.63 0.60</td>
<td></td>
<td>0.37 0.52</td>
<td></td>
<td>1.49 1.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.07) (0.07)</td>
<td></td>
<td>(0.06) (0.07)</td>
<td></td>
<td>(0.26) (0.39)</td>
<td></td>
</tr>
</tbody>
</table>

The simulation is repeated for 5,000 times. The average values are reported and the standard deviations are in parenthesis.
Figure 1: Unobservable quality of frontier products