How Licensing Resolves Hold-Up: Evidence from a Dynamic Panel Data Model with Unobserved Heterogeneity

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Abstract

In a patent thicket licensing provides a mechanism to either avoid or resolve hold-up. Firms' R&D incentives will differ depending on how licensing is used. In this paper we study the choice between ex ante licensing to avoid hold-up and ex post licensing to resolve it. Building on a theoretical model of a patent portfolio race, firms' choices of licensing contracts are modelled. We derive several hypotheses from the model and find support for these using data from the semiconductor industry. The empirical results show that firms' relationships in product markets and technology space jointly determine the type of licensing contract chosen. Implications for the regulation of licensing are discussed. We estimate a dynamic panel data model with unobserved heterogeneity and a lagged dependent variable. A method suggested by Wooldridge (2005) is employed to estimate a random effects probit model using conditional maximum likelihood.

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1 Introduction

In some high technology industries the process of research and development is comparable to the continuous extension of a pyramid through the addition of new building blocks at the top [Shapiro (2001)]. Here the pyramid serves as a metaphor for the cumulativeness of scientific research in complex product industries.[1]

Firms increasingly protect their contributions to this pyramid with patents. As a result several high technology industries are now affected by a "patent thicket" [Heller and Eisenberg (1998); Hall and Ziedonis (2001); Shapiro (2001)]. In a patent thicket patents protecting components of a technology are held by many rival firms. Whenever one of these firms uses this technology it is vulnerable to hold-up by firms holding blocking patents. Blocking patents are patents held by rival firms which cover part of a technology. In the face of blocking patents a firm's best defensive strategy is to hold a large portfolio of patents itself. This creates a strong bargaining position for the firm in any disputes with rivals. In a patent thicket all firms face the prospect of hold-up and have strong incentives to patent, which perpetuates the patent thicket. Hold-up in a patent thicket is resolved through the licensing of blocking patents. In consequence licensing is an increasingly important conduit for technological progress in industries affected by patent thickets.

In this paper we study how licensing is employed to resolve hold-up and how it affects firms' R&D incentives using data on contracts between semiconductor firms. We distinguish between licensing contracts signed before R&D investments take place (ex ante contracts) and those signed after such investments turn into granted patents (ex post contracts). Our data show licensing contracts are often forward looking (ex ante contracts)[2] and changes in the level of licensing are almost entirely due to changes in the level of ex ante licensing. Economic theory suggests that R&D incentives under ex ante licensing differ from those under ex post licensing. We, therefore, study the choice between ex ante and ex post licensing to examine the implications of patent thickets for firms' R&D incentives.

Firms in a patent thicket face uncertainty about the future strength of rivals' patent portfolios. Without licensing, blocking of patents within a patent thicket dulls R&D incentives, due to uncertain returns to R&D investment. With licensing, effects of blocking on R&D incentives depend on the type of license. Firms must choose between entering into "patent portfolio races"[3] and ex ante licensing which prevents such races. If firms choose patent portfolio races, then it is likely that ex post licensing is necessary due to existence of blocking patents. We model firms' choice between ex ante and ex post licensing. In particular patent portfolio races are modelled by allowing for complementarities between new patents and patent stocks in a patent race model. This introduces the possibility of blocking new

[1] A complex product is one which is based on many patents [Levin et al. (1987)]. Recently Cohen et al. (2000) show that firms in complex product industries primarily use the patent system for the purpose of forcing negotiations over access to others' patents.

[2] Examples of ex ante licenses may be found in Appendix C.

[3] This phrase is coined by Hall and Ziedonis (2001).

patents with existing patents. Then the choice between entry into a patent portfolio race and ex ante licensing can be studied as a function of the blocking strength of patent portfolios.

In our theoretical model we endogenize firms' R&D investments. These are driven by two R&D incentives of which only one depends on the strength of blocking patents. Under ex ante licensing the strength of blocking patents has no effect. Here the sole R&D incentive derives from raising profits by jointly improving a technology. Beath et al. (1989) refer to this as the *profit incentive*. In contrast, under ex post licensing a further incentive, the *competitive threat*, affects firms' R&D investments. This incentive arises from firms' desire to win the patent portfolio race which precedes ex post licensing. According to our model the strength of the *competitive threat* depends on the expected strength of blocking patents. The sign of this effect depends on whether firms compete in product markets or not. The model, therefore, shows that the choice of licensing contract depends on the strength of blocking patents as well as the product market relation between firms.

This theory of licensing type implies that firms avoid races against product market competitors who already hold strong blocking patents and enter into ex ante licensing contracts with them. Additionally, it also implies that, given strong blocking patents, product market complementors are more likely to enter into patent portfolio races. A first empirical test of the theory is derived from these predictions. This requires that we make use of data on product market and technology space interactions between licensing semiconductor firms.[4] A further test of the theory exploits the prediction that increases in the expected value of new patents reduce the probability of ex ante licensing.

We test our model using a dataset of licensing contracts announced between 1989 and 1999 in the semiconductor industry. A growing number of recent papers provide evidence of an emerging patent thicket in this industry [Grindley and Teece (1997); Shapiro (2001); Hall and Ziedonis (2001); Ziedonis (2004)]. Anand and Khanna (2000), who undertake a large sample study of licensing, also find that the semiconductor industry has one of the highest levels of licensing activity. This industry, therefore, provides a natural context in which to study the effects of licensing in a patent thicket. Furthermore, the effects of licensing on innovative activity in the semiconductor industry are of interest in their own right: Jorgenson (2001) argues that the semiconductor industry is one of the most important high technology industries, since its prices significantly affect many other downstream industries.

Hall and Ziedonis (2001) provide evidence that semiconductor firms are caught up in patent portfolio races. In contrast, previous theoretical and empirical research has focused on races at the level of individual patents. For instance, Cockburn and Henderson (1994) used highly disaggregated data in order to test whether patent races occur. To study the effects of patent portfolio races on licensing we use information about patent portfolios at the level of semiconductor technologies such as memory and microcomponents. Our empirical results

[4] In a similar vein Bloom et al. (2005) find that our understanding of the role of spillovers can be improved if we take account of firms' interactions in both the product market and technology space.

are consistent with patent portfolio racing.

The licensing data we study are puzzling: they show that overall licensing activity does not increase proportionally to the number of granted semiconductor patents. If more granted patents raise opportunities for hold-up such a proportional increase might be expected. Licensing activity increases strongly after 1989 and then falls quite sharply after 1994, even though patent grants increase over the whole sample period. The data also show that ex ante licensing is far more prevalent and volatile than ex post licensing. This last finding is somewhat surprising since previous literature on patent thickets has focused on ex post licensing or the formation of patent pools as a means of resolving the threat of hold-up [Grindley and Teece (1997); Shapiro (2001)]. Further investigation reveals that variation in the blocking strength of firms' patent portfolios by itself does not explain these trends.

As we can not directly observe firms' R&D spending a structural test of our model is out of reach. Instead we develop a latent variable representation of the choice between ex ante and ex post licensing which allows for dynamic effects. The latent variable model is derived from our theoretical model which endogenises R&D investment as a function of product market competition and the blocking strength of firms' patent portfolios. Additionally, our empirical model incorporates variation in transaction costs that arise from prior experience with licensing. We implement the latent variable model in a dynamic random effects probit model that allows for unobserved heterogeneity. In this implementation the dependent variable is the probability that firms choose ex ante licensing over ex post licensing.

In deriving our results we distinguish state dependence from dynamic responses to exogenous variables, caused by unobserved heterogeneity and serial correlation. We allow for state dependence because a pair of firms may sign multiple licensing contracts. State dependence arises if experience accumulated in earlier licensing contracts affects the current choice of licensing contract. Previous licensing contracts also affect firms' positions in technology space, which then affects expected profits from licensing. The empirical literature on licensing and R&D cooperation documents the importance of previous experience in determining firms' propensity to license or cooperate again [Fosfuri (2004); Hernán et al. (2003); Sakakibara (2002); Stuart (1998)]. Therefore, it is likely that the choice of licensing contract depends on whether two firms have had previous experience of licensing with one another.

We allow for lagged dependent and lagged exogenous variables in order to accurately test for state dependence. As firms may also differ in certain unobserved variables that influence their choices between ex ante and ex post licensing we take unobserved heterogeneity into account. If these unobserved variables are correlated over time and are not properly controlled for, a firm's previous experience may appear to be a determinant of future experience solely because it is a proxy for such temporally persistent unobservables. To make any inferences about true state dependence one must account for unobserved heterogeneity and other sources of serial correlation in unobservables.

In nonlinear dynamic panel data models with unobserved effects, treatment of the ini-

tial observations is a problem. Empirical analysis in this context is not trivial, as there are no known transformations - such as differencing - that eliminate the unobserved effects and result in usable moment conditions. Special cases have been worked out that eliminate the unobserved effects and result in usable moment conditions; compare Chamberlain (1992); Wooldridge (1997) and Honore and Kyriazidou (2000). Various ways to handle the initial conditions problem in parametric dynamic nonlinear models are suggested by Hsiao (1986). In this paper we use the method by Wooldridge (2005) who models the distribution of unobserved effects conditional on the initial values and any exogenous explanatory variables, see also Chamberlain (1980); Blundell and Smith (1991); Blundell and Bond (1998) and Arellano and Carrasco (2003). Rather than attempting to obtain the joint distribution of all outcomes of the endogenous variables, we apply a parametric approach and solve the initial conditions problem by specifying an auxiliary conditional distribution for the unobserved heterogeneity, conditional on the initial value and any exogenous explanatory variables. We then integrate out the unobserved heterogeneity of the joint density. We estimate a random effects probit model using conditional maximum likelihood.

The remainder of the paper is organised as follows: in Section 2 we describe licensing trends in the semiconductor industry. In Section 3 we introduce our theoretical model. In the following section we discuss its empirical implementation. Then in Section 5 we discuss our results. Finally, Section 6 concludes.

2 Licensing in the semiconductor industry

In this section we describe observed licensing behaviour. We constructed a dataset comprised of 847 records of licensing contracts between semiconductor firms. It contains information about the purpose of the license and data on firms' revenues, market shares and semiconductor patents. A detailed description of the data is provided in Appendix B. In this section we describe the data and determine whether the blocking strength of firms' patent portfolios explains the choice of licensing contract by a pair of firms.

Figure 1a
Growth of revenues and firm numbers in the semiconductor industry

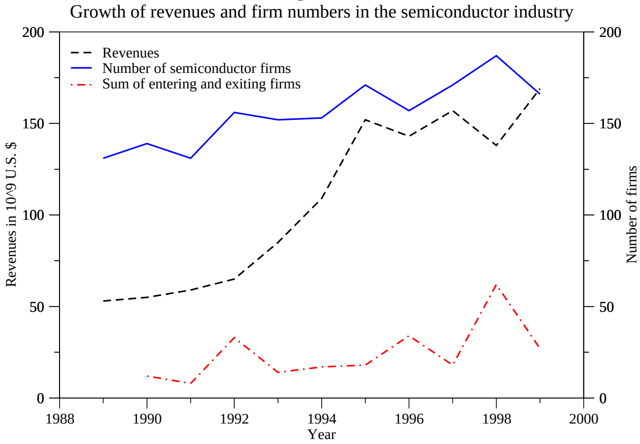


Figure 1b
Licensing and patenting activity in the semiconductor industry

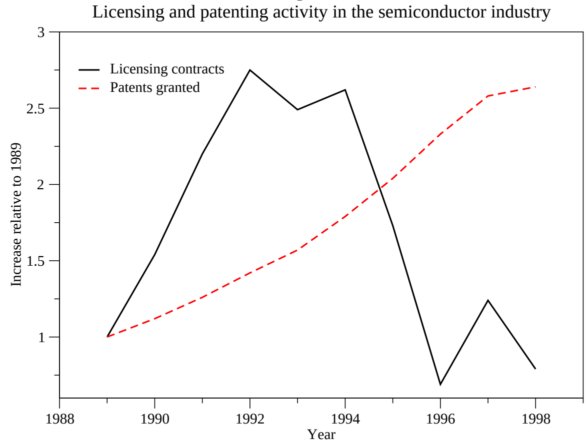


Figure 1a shows that total revenues of all semiconductor firms grew substantially over the period of our sample. Mirroring this there was also a large increase in the number of active semiconductor firms. However the figure also demonstrates that aggregate revenue almost stopped growing after 1996. This coincided with increased turbulence in the industry, as a much larger proportion of semiconductor firms was affected by entry and exit than had previously been the case.

The semiconductor industry also experienced a strong surge in patenting activity after 1985 [Hall and Ziedonis (2001); Ziedonis (2003, 2004)]. Figure 1b provides information on the level of granted patents and licensing contracts relative to 1989. The number of new patents granted to semiconductor firms more than doubled over the period of our sample. This development has been carefully investigated by Hall and Ziedonis (2001) who argue that it is due to strategic patenting in the face of an emerging patent thicket. Surprisingly, the increase in patenting by semiconductor firms does not lead to a proportionate increase of licensing amongst these firms. As Figure 1b shows the number of new licensing contracts amongst semiconductor firms in our sample shows no obvious relation to the increase in granted patents. This is surprising because we might expect there to be a greater need for licensing as the number of patents grows.[5]

Figure 2a
The frequency of licensing per firm in the semiconductor industry

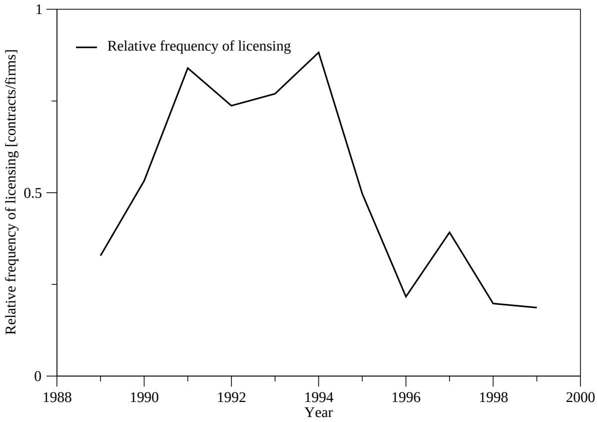


Figure 2b
Total ex ante and ex post licensing contracts in the semiconductor industry

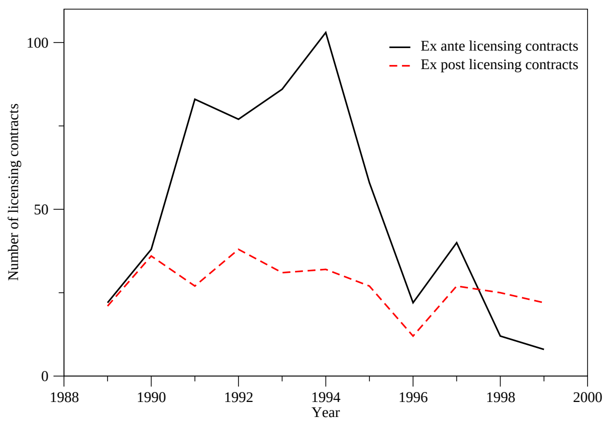


Figure 2a above shows the average number of licensing contracts per firm in the semiconductor industry. The figure displays a hump shape just as the absolute number of licensing contracts does. This rules out an explanation of the number of licenses based on the number of semiconductor firms. Between 1991 and 1994 there were almost as many licensing contracts as firms in the industry. The decline in licensing activity after 1994 also remains

[5] Information on the duration of a subset of licensing contracts in our data suggests that these contracts last for roughly 5 years. We used this estimate and similar ones to simulate the stock of licensing contracts based on our data. This shows that the reduction in licensing contracts after 1994 is so large that the stock of contracts also diminishes after that date. Therefore the changes we observe in new licensing contracts are not the result of a saturation of the demand for licensing contracts

clearly visible.[6]

Next we introduce the distinction between ex ante and ex post licensing. Figure 2b shows that ex ante licensing is far more variable over the period of our sample than ex post licensing. As noted in the introduction this finding is surprising in light of the previous literature

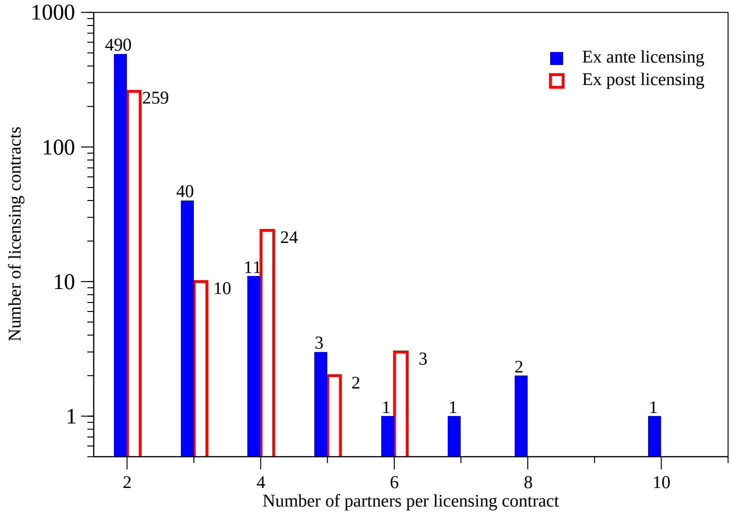
To gain a better understanding of what underlies the patterns of ex ante and ex post licensing illustrated in Figures 2a and 2b we present information on the top 20 innovating firms in the semiconductor industry in Table 1. The table provides information on the number of patents granted to each firm, their cumulative revenues and their average market shares between 1989 and 1999. Furthermore, we report the percentage of licensing contracts of both types, each firm was a party to. In each column the top three firms are highlighted in boldface.

Table 1 shows that Texas Instruments and Intel account for over one fifth of all ex post licensing agreements.[7] Previous studies [Grindley and Teece (1997); Shapiro (2001, 2003)] tended to focus on these firms which may explain why they devote less attention to ex ante licensing. The number of ex ante licensing agreements is spread relatively evenly across the represented firms. In spite of this difference between ex ante and ex post licensing it is clear that nearly all of the represented firms engage in both types of licensing to a significant degree. Twenty nine percent (29%) of the contracts in our sample are signed by firms with experience of both ex ante and ex post licensing. This suggests that the observed trends are not the result of greater licensing activity by a group of firms specialising in ex ante licensing; rather, we must focus on the choice that all firms make between ex ante and ex post licensing.

The data show significant differences between ex ante and ex post licensing by semiconductor firms. To pursue the comparison of ex ante and ex post licensing we also investigate the number of firms involved in each licensing contract. As the histogram in Figure 3 illustrates, the vast majority of contracts in this sample are bilateral. Nonetheless a significant proportion (11.6%) are between more than two firms.

Figure 3

Distribution of participant numbers in ex ante and ex post licensing contracts



An aggregate measure of the strength of the patent thicket in form of a patent count does not explain the development of licensing between semiconductor firms in aggregate. It is also unrelated to the choice between ex ante and ex post licensing. We, therefore, turn to two

[7] No agreements between the two firms are recorded in our data.

measures that capture aspects of the patent thicket at the level of pairs of licensing firms. The construction of these measures is set out below, in section 4.2. First, we construct a measure that captures the *blocking strength* (B) of firms' patent stocks. It represents the likelihood that firm-pairs block each other's semiconductor patents. This measure increases if the two firms have higher shares of total industry patent applications in the same patent classes. The blocking strength of firms' patent applications is plotted separately for firm-pairs that chose ex ante and ex post licensing contracts, below, in Figure 4a. The figure consists of a box-whisker plot of the blocking strength of patent stocks by year. It shows that blocking by itself is unlikely to explain firms' choices between ex ante and ex post licensing.

In Figure 4b we present a similar graphical analysis for a measure of the average complementarity between patent applications of one firm and the patent stock of the other firm in a pair. We call this *forward complementarity* (C) to emphasise that it is the complementarity between new patents and existing patent stocks. Variation in *forward complementarity* might be expected to explain the propensity of a firm-pair to license. The figure does not reveal any clear trends that explain the observed hump in licensing nor does it reveal differences between firm-pairs choosing to license ex ante and ex post. This indicates that a simple explanation of semiconductor firms' licensing behaviour is unlikely to exist. Therefore, the remainder of this paper provides an explanation of licensing behaviour which is based on a model of choice between ex ante and ex post licensing in the context of a patent thicket.

Figure 4a

Blocking strength of patent stocks for ex ante and ex post licensing contracts

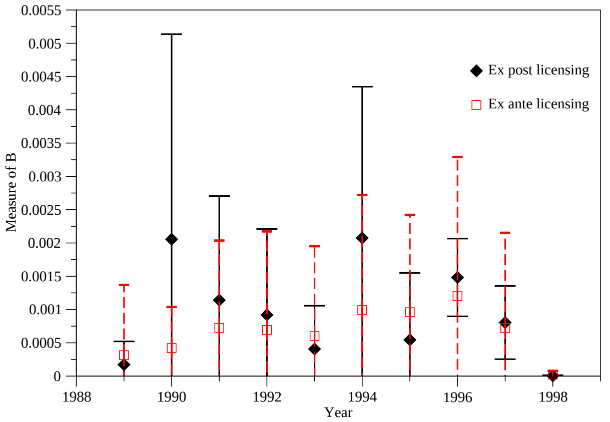
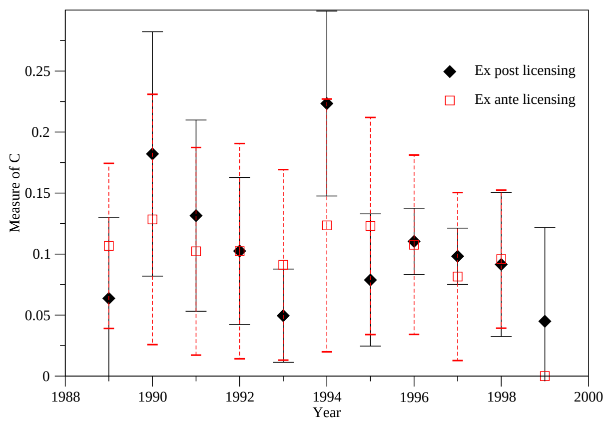


Figure 4b

The forward complementarity for ex ante and ex post licensing



We end this section by providing descriptive statistics for the firms in our sample, distinguishing between firms that licensed ex ante and firms that licensed ex post. This table shows no obvious differences between the firms that undertake ex ante and ex post licensing in our data. This is partly due to the fact that some firms engage in both activities as previously discussed. The average number of firms involved in a contract is between two and three. The average firm engaged in approximately 6 contracts between 1989 and 1999. The average firm engaging in ex ante (ex post) licensing was granted 128 (137) patents and its patent stock attracted a total of 1,056 (1,145) citations over the sample period. All of these variables are highly skewed.

Table 2: Sample statistics for firms by licensing contract type

	Ex post licensing					Ex ante licensing				
Variable	N	Mean	Std. dev.	Min.	Max.	N	Mean	Std. dev.	Min.	Max.
Number of parties	771	2.47	0.98	2	6	1,264	2.39	1.16	2	10
Total contracts	771	6.35	11.02	1	44	1,264	5.57	7.25	1	38
Market shares (%)	532	2.9	3.3	0	16.4	703	2.9	2.9	0	16.4
Patent grants	504	128	198	0	873	657	137	192	0	873
Forward citations	504	1,056	1,341	0	6,282	657	1,145	1,413	0	6,282

3 Modelling the choice of licensing type

In this section we describe our theoretical model of the choice between ex ante and ex post licensing. We derive hypotheses about the effects of exogenous variables on the expected value of ex ante and ex post licensing (V^a, V^p). An example of the model assuming a specific functional form for R&D costs is presented in Appendix A. A general treatment of the model can be found in Siebert and von Graevenitz (2006).

Define the premium to licensing ex ante as:[8]

$$\Pi_{k,t} = \left(V^a_{k,t} - T^a_{k,t}\right) - \left(V^p_{k,t} - T^p_{k,t}\right) \ , \tag{1}$$

where the premium to ex ante licensing ($\Pi_{k,t}$) for the firm-pair k at time t is the difference between the surpluses from licensing ex **a**nte and ex **p**ost. Each of these surpluses is the difference between the expected value of licensing ($V^a_{k,t}, V^p_{k,t}$) and the transaction costs attached to licensing ($T^a_{k,t}, T^p_{k,t}$). If the premium is positive ($\Pi_{k,t} > 0$) firms will license ex ante.

The expected values of ex ante and ex post licensing ($V^a_{k,t}, V^p_{k,t}$) are functions of the level of R&D investment. Firms' R&D investment incentives depend on their interactions in product markets and interdependencies between their patent portfolios. We model the expected values of licensing ($V^a_{k,t}, V^p_{k,t}$) in a game theoretic model of licensing and R&D investment to capture these effects. This model does not include transaction costs of licensing ($T^a_{k,t}, T^p_{k,t}$), which are independent of variables determining the expected values of licensing ($V^a_{k,t}, V^p_{k,t}$).

Our model of licensing and R&D investments is based on a patent race model as pioneered by Loury (1979) and Lee and Wilde (1980). In our model firms that do not license ex ante, race for ownership of a technology. Ownership of the technology is based on ownership of a patent portfolio protecting the technology from hold-up. The greater the quality of this patent portfolio the stronger the winning firm's bargaining power should hold-up occur. The Poisson distributed arrival time in our model represents the point in time at which the

[8] Notice that this model is conditional on the fact that firms license. We explicitly assume that licensing is always more profitable than not licensing.

winning firm has developed the technology sufficiently to use it.[9] At this time the winning firm must license any blocking patents held by rival firms. Therefore rival firms capture some of the surplus created by the new technology. In deriving our theoretical results we assume losing firms will always remain active competitors in the product market. Winning the race for a technology mainly shifts a greater proportion of industry profits towards the winner.

Given this setting the strength of a firm's R&D incentives depends on the form of licensing contract chosen. Following Beath et al. (1989) we identify two innovation incentives at work in a model of racing: *competitive threat* and *profit incentive*. Under ex ante licensing[10] firms contract to share the new technology in the future. Here the arrival of the technology only has the effect of raising both firms' profits and only the *profit incentive* is at work. In contrast, under ex post licensing both innovation incentives determine the level of R&D investment. In addition to the *profit incentive* a *competitive threat* arises since the winner receives greater profits than the loser. This creates a strong incentive to win the race. R&D investment under ex post licensing therefore exceeds R&D investment under ex ante licensing.

The discussion in the previous paragraph highlights that any differences between the expected values of ex ante and ex post licensing must derive from the *competitive threat*. Variation in this incentive leads only to variation in the expected value of ex post licensing. Conversely, variation in the *profit incentive* affects the expected values of both alternatives. Utilising a comparative statics result derived by Nti (1997) for patent race models we derive the effects of variation in the *competitive threat* on the expected value of ex post licensing. He shows that increases in the value of winning the patent race increase both the level of R&D investment during the race and the *expected* value of winning the race.

Here we turn to the first comparative statics result which emerges from our theoretical model. We consider the effects of variation in the value of the new technology on the choice between ex ante and ex post licensing. In our model the ex ante premium declines as the value of a new technology increases. This relationship arises because the expected value of ex post licensing grows faster than that of ex ante licensing when the value of the new technology increases.

We measure the value of a new technology with the help of two factors. First, we note that a new technology is more valuable if it is a stronger complement to existing technologies. We call this the *forward complementarity* (C) of the technology. Then, we note that the value of a technology also grows if the market value of the products which it improves is greater. We represent this market value by (W). We measure variation in the value of a new technology

[9] We assume that firms' investments in development of the technology are constant over time. Doraszelski (2003) has recently introduced a model of patent races in which the investments need not be constant over time. Incorporating this feature into the model would go far beyond what is observable in our data. Therefore we maintain the simpler framework of constant investments.

[10] The literature on research joint ventures, e.g. Kamien et al. (1992), identifies several possibilities for ex ante contracts depending on whether firms share research results only or also cooperate on R&D. Our prediction for ex ante licensing is robust to variation in the exact assumptions made about R&D cooperation.

through the product of these factors. The discussion above implies that:

Hypothesis 1
The probability of observing ex ante licensing falls as the value of a new technology increases.

Then a linear approximation of our model takes the following form:

$$V^a_{k,t} - V^p_{k,t} = \gamma_0 + \gamma_1 C_{k,t} W_{k,t} + \gamma_2 (C_{k,t} W_{k,t})^2 + Z_{k,t} \qquad , \tag{2}$$

where γ_0, γ_1 and γ_2 are parameters to be estimated and $Z_{k,t}$ captures all the effects of the blocking strength of patent stocks in a pair of firms at a given time. We introduce a quadratic term into our model in order to test Hypothesis 1 against a U-shaped functional form as well. Hypothesis 1 implies that $\gamma_1 C_{k,t} + 2\gamma_2 C^2_{k,t} W_{k,t} < 0$.

We turn now to the second comparative statics result derived from our model. This captures the effects of variation in the blocking strength of patent portfolios on firms' propensity to license ex ante. Under ex ante licensing variation in the blocking strength of existing patent stocks $(B_{k,t})$ has no effect as future patents are shared and hold-up is ruled out by contract. Ex post licensing, in contrast, occurs because the firm holding a new technology desires to resolve the hold-up problem. In this case firms use their patent stocks as bargaining chips. The size of the "pie" they bargain over will depend on the blocking strength of existing patent stocks. As the pie is divided between the winner and loser(s) of the race, both sides' payoffs from racing also depend on the blocking strength of existing patent stocks. Thus the prize being offered in the race for the new technology is a function of this parameter.

The effects of variation in the blocking strength $(B_{k,t})$ on the ex ante premium depend on the number of contracting parties $(N_{k,t})$ and the product market relation between them. We distinguish a number of cases. The simplest case is that of two firms which are product market rivals.

In this case a higher ability to block a new technology lowers the value of winning it. Blocking has two countervailing effects: a direct effect where blocking lowers the outside option of the winning firm; an indirect effect where blocking increases the size of the pie the winner and loser bargain over ex post. In Appendix A we show this indirect effect does not compensate the direct effect. Therefore, under ex post licensing stronger blocking reduces the value of winning the race for the new technology and also the expected value of ex post licensing. We derive the following hypothesis:

Hypothesis 2
If two firms, who compete in the product market, choose when to contract, stronger blocking patents reduce the expected value of ex post licensing.

We refer to this case as that of *blocking in a competitor pair*. Such blocking raises the ex ante licensing premium.

A more complex case arises when firms produce complementary products. Complementarity in the product market implies that one firm's profits increase if its partners become more competitive. As a consequence the owner of a valuable new patent has a strong interest to make this available to any partner firms that produce complementary products and could benefit from the patent. In spite of this interest the firm may still seek to appropriate as large a share of the resulting surplus as possible. As before an increase in the blocking strength of existing patents lowers the outside option of the winning firm. However, we demonstrate in Appendix A that the indirect effect, which arises from the growth of the bargaining pie, will more than compensate the direct effect if more than two firms contract over the new technology ex post. Therefore, we advance a third hypothesis:

Hypothesis 3

For technology races with more than two competitors producing complementary products the expected value of ex post licensing is increasing in the strength of blocking patents.

We refer to this case as that of *blocking in a complementor group* which lowers the premium to ex ante licensing.

The two previous hypotheses depend on the values of the blocking strength of patent portfolios $B_{k,t}$, the number of rivals in technology space $N_{k,t}$ and on the product market relation between the firms in a licensing contract. Below we make use of a dummy variable D^N which measures whether there are more than two ($D^N = 1$) or exactly two firms in a contract. For simplicity we also introduce a dummy variable which captures whether firms produce substitute products $(D^S = 1)$ or not. A linear approximation of the effects of the blocking strength of patent stocks on the ex ante premium takes the following form:

$$Z_{k,t} = \gamma_3 \underbrace{B_{k,t}(1-D^N_{k,t})D^S_{k,t}}_{\text{a competitor pair}} + \gamma_4 \underbrace{B_{k,t}D^N_{k,t}(1-D^S_{k,t})}_{\text{a complementor group}} \tag{3}$$

Blocking in:

$$+\gamma_5 \underbrace{B_{k,t}D^N_{k,t}D^S_{k,t}}_{\text{a competitor group}} + \gamma_6 \underbrace{B_{k,t}(1-D^N_{k,t})(1-D^S_{k,t})}_{\text{a complementor pair}} \quad ,$$

where the parameters $\gamma_3 - \gamma_6$ remain to be estimated. Greater blocking in a *competitor pair* implies that $\gamma_3 > 0$ and in a *complementor group* it implies that $\gamma_4 < 0$. Equation (3) shows that in addition to the cases of blocking in a *competitor pair* and *complementor group* we must also consider those of a *competitor group* (γ_5) and *complementor pair* (γ_6). We cannot derive restrictions on the signs of these parameters (γ_5, γ_6) from our theoretical model.

4 The empirical model: derivation and implementation

In this section we develop a latent variable model of the premium to ex ante licensing that encompasses our hypotheses. We go on to discuss how variables necessary for its estimation are constructed and provide descriptive statistics for these variables. Finally we derive an econometric specification for our model and consider issues that arise in estimating it.

4.1 A latent variable model of the premium to ex ante licensing

The premium to ex ante licensing shown in equation (1) is unobserved and we treat it as a latent variable $(\Pi^*_{k,t})$ here:

$$\Pi^*_{k,t} = \left(V^a_{k,t} - V^p_{k,t}\right) - \left(T^a_{k,t} - T^p_{k,t}\right) + u_{k,t} \ , \tag{4}$$

where $u_{k,t}$ is a continuously distributed error term with mean zero. Where the premium to ex ante licensing is positive we observe ex ante licensing, otherwise we observe ex post licensing. In the previous section we derived a linear approximation of the first term on the right hand side of equation (4).

As the transaction costs of licensing are not directly observed we use a proxy measure. Care must be taken, as previous licensing experience, between a pair of firms, introduces state dependence and unobserved heterogeneity into our econometric model.

State dependence in licensing decisions Previous experience with a particular firm may reduce the transaction costs of licensing with that firm again in the future, especially if the licensing contract is of the same type. The empirical literature on R&D cooperation has shown that the probability of R&D cooperation or licensing increases in the amount of earlier cooperation the two firms have undertaken.[11] Therefore we must consider the possibility of state dependence in the choice of licensing contract. We allow for this by introducing a lagged dependent variable into our empirical model.

The extended latent variable model We insert equations (2) and (3) in the latent variable model of equation (4). This yields an extended model combining our linear approximation of $(V^a_{k,t} - V^p_{k,t})$ and the transaction costs effects:

$$\begin{aligned}\Pi^*_{k,t} = &\underset{-}{\gamma_1} W_{k,t}C_{k,t} + \underset{+}{\gamma_2}\left(W_{k,t}C_{k,t}\right)^2 + \underset{+}{\gamma_3} B_{k,t}(1-D^N_{k,t})D^S_{k,t} + \underset{-}{\gamma_4} B_{k,t}D^N_{k,t}(1-D^S_{k,t}) + \gamma_5 B_{k,t}D^N_{k,t}D^S_{k,t} \\ &+ \gamma_6 B_{k,t}(1-D^N_{k,t})(1-D^S_{k,t}) + \underset{+}{\gamma_7} L^a_{k,t} + \underset{-}{\gamma_8} L^p_{k,t} + \rho\Pi_{k,t-1} + c_k + u_{k,t} \quad ,\end{aligned} \tag{5}$$

where c_k represents unobserved heterogeneity and ρ is the parameter for the lagged dependent variable. The specification of the empirical model and its estimation are discussed in

[11] This finding is reported by Hernán et al. (2003), Vonortas (2003), Sakakibara (2002) and Stuart (1998).

section 4.4 below.

4.2 Definitions of variables

In this section we describe the explanatory variables employed in our model. The data we use to build these variables are described in Appendix B. All our variables characterise pairs of licensing firms. Firm-pairs are characterised by computing the average of the individual firms' characteristics.

The dependent variable - $\Pi_{k,t}$ Our dependent variable measures whether the firm-pair k entered into an ex ante licensing contract at time t $(\Pi_{k,t} = 1)$ or an ex post licensing contract $(\Pi_{k,t} = 0)$.

The strength of blocking patents - $B_{k,t}$ This variable captures the extent to which a firm's existing patent stocks are a basis for hold-up of their rivals' new patents. We build this measure from firms' shares of patents in nine different patent classes[12] (a), to which all semiconductor patents may be assigned. We assume firms' patent stocks are more likely mutually blocking if their average shares of patents over these classes are high. Our measure of $B_{k,t}$ for pair k at time t is defined as follows:

$$B_{k,t} = \sum_{i=1}^{2}\sum_{a=1}^{9} \frac{P_{iat}}{\sum_{l=1}^{n} P_{lat}} * \frac{P_{iat}}{\sum_{a=1}^{9} P_{iat}} * \frac{P_{jat}}{\sum_{a=1}^{9} P_{jat}} \quad , \tag{6}$$

where P_{iat} is the count of the number of patents of firm i in patent class a at time t and l stands for the number of firms active in a patent area. This measure captures a weighted sum of each firm's share of patents in the nine patent areas. There are two weights: the share of the firm's patenting activity in that area and the share of its partner's patenting activity in that area. To characterise the firm-pair we sum the two firms' weighted patent area shares.

This measure is largest when two firms have all their patents in the same patent classes. The measure varies between a minimum of zero, all their patents in different patent classes, and a maximum of one, all patents in one patent class. The measure is monotonically increasing as the concentration of patents in one patent class increases.

The forward complementarity - $C_{k,t}$ This variable captures complementarity between the existing patent stocks held by each firm and new patents granted to its partner(s) in a cooperative agreement. In our theoretical model a greater complementarity between new patents and existing patent stocks induces higher quality of the ex post patent stocks. In order to capture this dimension of quality of patents and patent stocks we employ counts of

[12] These patent classes are identified by Hall et al. (2001) as the classes $257, 326, 438, 505$ (semiconductors), $360, 365, 369, 711$ (memory) and 714 (microcomponents).

forward citations of firms' patents in our measure of *forward complementarity* (C).[13] Our measure of C for the pair k and time t is defined as follows:

$$C_{k,t} = \sum_{a=1}^{9} \left[\frac{PC_{iat}}{\sum_{l=1}^{n} PC_{lat}} * \frac{\sum_{\tau=0}^{t-1} PC_{ja\tau}}{\sum_{a=1}^{9} \sum_{\tau=0}^{t-1} PC_{ja\tau}} + \frac{PC_{jat}}{\sum_{l=1}^{n} PC_{lat}} * \frac{\sum_{\tau=0}^{t-1} PC_{iat}}{\sum_{a=1}^{9} \sum_{\tau=0}^{t-1} PC_{ia\tau}} \right] , \tag{7}$$

where PC_{iat} is the number of forward citations received by patents of firm i in patent area a. We divide the count of forward citations to firm i's patents by the overall count of forward citations to all firms' patents. This yields a measure of the relative quality of each firm's new patents in year t. This measure is multiplied with a similarly constructed measure of the relative quality of the partner firm's patent stock. We calculate these products for each firm by patent area. Then we sum these products for the firm's in a pair and across all nine patent areas.

This measure captures both mutual complementarities and one-way complementarity between new patents of one firm and the patent stock of the other. The measure has a a minimum of zero, if neither firm received, or is receiving, any citations. It has a maximum of 9, if, one firm's patents receive all citations in year t and its partner's patents received all previous citations.

The value of innovation by a firm-pair - $W_{k,t}$ This variable measures a firm-pair's expected value of owning a new patent. It measures, for each patent area, total citations received by the pair's stock of patents, relative to total citations received by all firms. Our measure of $W_{k,t}$ for the pair k at time t is defined as follows:

$$W_{k,t} = \sum_{i=1}^{2} \sum_{a=1}^{9} \frac{\sum_{T=0}^{t} PC_{iat}}{\sum_{T=0}^{t} \sum_{l=1}^{n} PC_{lat}} . \tag{8}$$

We sum across all patent areas a and the two firms in the pair. In using this measure we implicitly assume a more valuable existing patent stock implies future additions to that stock will also be of greater value.

The value of innovation measure varies between a minimum of zero, no citations at all, and a maximum of 9, all citations in all the patent classes.

Producers of substitute or complementary products - D^S This variable measures the extent to which firms are producers of complementary or substitute products. Our hypotheses regarding firms' propensity to license ex ante depend on whether firms are competitors or complementors in the product market. A firm's sales are allocated over three segments

[13] Counts of forward citations are an imperfect but frequently employed measure of the quality of patent stocks. The measure was first investigated by Trajtenberg (1990). Recently Lanjouw and Schankerman (2004) found it to be the best performing of several alternative measures of patent quality.

of the semiconductor industry (memory, microcomponents, others). We assume firms are competitors if both have sales in the same segment of the semiconductor industry.

Transaction costs of ex ante and ex post R&D cooperation Our data do not contain any direct measures of licensing transaction costs. However, we expect previous experience of licensing ex ante or ex post to reduce the transaction costs of choosing such a licensing contract again. Therefore, we introduce counts of previous experience with ex ante ($L^a_{k,t}$) and ex post ($L^p_{k,t}$) licensing contracts as proxies of firms' transaction costs of licensing ex ante ($T^a_{k,t}$) and ex post ($T^p_{k,t}$).

The number of firms sharing a new innovation -N This variable measures the number of firms jointly choosing between an ex ante and an ex post licensing contract. We construct a dummy variable ($D^N = 1$) if we observe more than two partners to a licensing contract.

Further control variables

- *Average market shares*: We include this variable to control for the average size of the firms in a licensing contract. Firm size has significant effects in regressions seeking to explain participation in licensing or R&D cooperation.
- *Differences in market shares*: Stuart (1998) shows licensing agreements with a highly visible firm can bestow prestige on a smaller partner firm. He finds prestige has a strong positive effect on firms' propensity to license. In order to control for this effect which is not captured by our theoretical model we proxy firms' importance in the industry by their average market shares. The difference between firms' average market shares can then be taken as a measure of additional prestige which licensing bestows on the smaller partner in the contract.
- *Aggregate revenues*: We include this variable to control for changes in the demand for semiconductor products.

4.3 Descriptive statistics

Table 3 below provides descriptive statistics for pairs of licensing firms observed in our data. In the first three lines of Table 3 the means of the variables do not differ strongly between firm-pairs that license ex ante and ex post. The lower part of the table shows that more interesting differences emerge once we interact the variables in the way suggested by our theoretical model. In particular the means of the interaction terms $B(1-D^N)D^S$ (*blocking in a competitor pair*) and $BD^N(1-D^S)$ (*blocking in a complementor group*) differ substantially if we compare firm-pairs engaged in ex ante and ex post licensing.

Just as predicted by Hypothesis 2, ex ante licensing is more probable than ex post licensing when two competing firms license. Similarly ex post licensing is more probable than ex

ante licensing when a group of producers of complementary products license. This is the prediction of Hypothesis 3.

Table 3: Sample statistics for firm-pairs by licensing contract type

	Ex ante licensing ($N = 321$)				Ex post licensing ($N = 258$)			
Variable	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
B	0.00075	0.00148	0	0.010	0.00150	0.00274	0	0.014
C	0.10625	0.08529	0	0.354	0.12302	0.08654	0	0.416
W	0.02835	0.02179	0	0.093	0.03200	0.02269	0	0.113
CW	0.00426	0.00549	0	0.030	0.00526	0.00578	0	0.028
blocking in a:								
competitor pair	0.00023	0.00083	0	0.006	0.00009	0.00039	0	0.002
complementor group	0.00001	0.00006	0	0.001	0.00003	0.00024	0	0.003
competitor group	0.00046	0.00132	0	0.010	0.00091	0.00180	0	0.009
complementor pair	0.00006	0.00024	0	0.002	0.00005	0.00013	0	0.001
$\Pi_{k,0}$	0.03738	0.19000	0	1	0.08527	0.27983	0	1
L^p	6.68692	6.54069	0	37.500	8.33527	8.16149	1	38.500
L^a	9.41122	6.87300	1	36	8.13760	6.66817	0	28.500
Average market shares	0.03074	0.01926	0	0.099	0.03198	0.02358	0	0.083
Difference market shares	0.03241	0.02979	0	0.164	0.02874	0.02913	0	0.163
Aggregate revenues 10^9	94.71351	36.95310	53	152.875	85.57402	37.17869	53	169.311
D^N $(N > 2)$	0.46729	0.49971	0	1	0.53488	0.49975	0	1
$(1 - D^S)$ (Complements)	0.38941	0.48838	0	1	0.38372	0.48724	0	1

4.4 Specification of the empirical model

In this section we discuss the specification of our econometric model and briefly consider sample selection issues. The econometric model is a dynamic binary choice model which allows for state dependence. In this model state dependence arises if previous licensing in a firm-pair lowers transaction costs.

The estimation of dynamic binary response models is beset with difficult econometric problems. In particular, it is likely that we do not observe all factors which affect firms' choices to license ex ante. As a consequence there is unobserved heterogeneity in our data. In settings in which dynamic effects are likely to be important, controlling for unobserved heterogeneity is crucial. If unobserved heterogeneity is ignored it is impossible to exclude that observed state dependence is a "spurious" consequence of serial correlation induced by unobserved heterogeneity.

"Spurious" state dependence arises where there is correlation between the initial condi-

tion $\Pi_{k,0}$ and the unobserved heterogeneity. Hsiao (1986) discusses several solutions to deal with this initial conditions problem. One solution deals with possible correlation between the initial condition and the unobserved heterogeneity by integrating out unobserved heterogeneity. To do so it is necessary to specify the distribution of the initial condition, conditional on unobserved heterogeneity. This distribution is not known and any misspecification thereof yields an erroneous model. Heckman (1981) suggests pursuing this approach by approximating the conditional distribution of the initial condition. Unfortunately this approach is computationally intensive.

An alternative approach to dealing with the initial conditions problem that is unaffected by this problem is suggested by Honore and Kyriazidou (2000). They suggest a fixed effects estimator in order to estimate a dynamic logit model with strictly exogenous regressors. While this approach does not require distributional assumptions on the unobserved heterogeneity or the initial condition, it suffers from the drawback that partial effects on the response probability are not identified.

We follow Wooldridge (2005) who suggests modelling the distribution of the unobserved heterogeneity conditional on the initial value and exogenous explanatory variables. He shows that this approach is simpler to implement and allows one to recover average partial effects quite easily. This advantage must be weighed against possible misspecification of the distribution of unobserved heterogeneity and a resulting inconsistency of one's parameter estimates.

In order to allow for the effects of unobserved heterogeneity we estimate the following dynamic random effects probit model:

$$P\left(\Pi_{k,t}=1|\,\Pi_{k,t-1},.,\Pi_{k,0},\boldsymbol{z_{k,t}},c_k\right)=\Phi\left(\boldsymbol{z_{k,t}\gamma}+\rho\Pi_{k,t-1}+c_k\right) \tag{9}$$

where $\Pi_{k,t}=1$, if a firm-pair (k) licenses ex ante in period t, $\boldsymbol{z_{k,t}}$ is a vector of strictly exogenous explanatory variables, ρ is the parameter indicating the presence of state dependence and c_k represents the effects of unobserved heterogeneity. Φ denotes the standard normal cumulative distribution function. The vector of exogenous variables $\boldsymbol{z_k}$ contains the explanatory variables set out in equation (5) above.

We estimate the model using conditional maximum likelihood. Let $c_k|\Pi_{k,0},\boldsymbol{z}_k\sim$ Normal $(\delta_0+\delta_1\Pi_{k,0}+\boldsymbol{z}_k\boldsymbol{\delta}_2,\sigma_a^2)$, where $\boldsymbol{z}_k$ is the row vector of all explanatory variables in all time periods. Wooldridge (2005) shows that, given an error term $a_k|(\Pi_{k,0},\boldsymbol{z}_k)\sim$ Normal $(0,\sigma_a^2)$, $\Pi_{k,t}$ given $(\Pi_{k,t-1},...,\Pi_{k,0},\boldsymbol{z}_k,a_k)$ follows a probit model with response probability

$$\Phi(\boldsymbol{z_{k,t}\gamma}+\rho\Pi_{k,t-1}+\delta_0+\delta_1\Pi_{k,0}+\boldsymbol{z_k}\delta_2+a_k+u_{k,t})\;. \tag{10}$$

To estimate this model we add $\Pi_{k,0}$ and $\boldsymbol{z_k}$ as additional explanatory variables in each time period and apply random effects probit to estimate $\boldsymbol{\gamma},\rho,\delta_0,\delta_1,\delta_2$ and σ_a^2.

In our theoretical model we condition on the fact that licensing is always preferred to not licensing. This assumption keeps the analysis simple and tractable as it allows us to focus only on firms that license. Doing so we assume that the subset of semiconductor firms that engage in licensing is consistent with the whole underlying population of the semiconductor firms. The conditioning assumption enables us to deal with problems introduced by state dependence in the choice of licensing contract and unobserved heterogeneity. However this approach will give rise to a sample selection bias if firms that license represent a non randomly selected sample. This problem does not arise if the selection mechanism is exogenous. We tested and confirmed that there is no significant correlation between residuals of (i) a probit, dependent variable: whether to license or not, and (ii) a further probit, dependent variable: whether to license ex ante or ex post.

5 Results

In this section we present and discuss results of estimating the specification (Equation (10)) discussed in section 4.4. Below, we refer to this as specification (3). We also estimate a binary choice model both with, specification (2), and without, specification (1), a lagged dependent variable. We include specification (1) to establish whether controlling for unobserved heterogeneity is necessary. Specification (2) provides insight into state dependence in the choice of licensing contracts. It should be borne in mind that evidence for unobserved heterogeneity in the data would indicate inconsistencies in estimating specification (2).

The results from estimation of these three specifications may be seen in Table 4 on the following page. We report both the parameter estimates and corresponding elasticities. Elasticities in specification (3) are averages at the sample mean. The first six parameters set out in the table capture hypotheses 1-3. The effects of previous licensing experience are captured by the variables L^a, L^p and the lagged dependent variable ($\Pi_{k,t-1}$).

Table 4 shows the signs and significance of all variables of interest are stable across the three specifications. Of the three specifications estimated, we concentrate on the third because it allows for state dependence and deals with the initial conditions problem in the manner suggested by Wooldridge (2005).

Our preferred specification, (3), is discussed in greater detail below. The discussion deals with each theoretical prediction discussed in section 3 above and the effect of transaction costs on the choice of licensing contract. Additionally, we discuss a test of the model's predictive power.

Predictions on the expected value of licensing Hypothesis 1, which refers to effects of the expected value of a technology on the ex ante premium, is captured by the parameters CW and $(CW)^2$. These are significant at the 1 and 5 percent levels, respectively. The minimum point of this quadratic function lies at $CW = 0.017$ and the quadratic crosses the x-axis at

$WC = 0.034$ which is far beyond the sample mean of WC at 0.0047.

Table 4: Results - Dependent variable $\Pi_{k,t}$

Explanatory variables	(1)	Elasticity	(2)	Elasticity	(3)	Elasticity
CW	-72.055***	-0.504	-114.672***	-0.834	-119.354***	-0.839
	(27.486)		(30.057)		(39.326)	
$(CW)^2$	2167.555		3124.818**		3549.572**	
	(1328.844)		(1376.596)		(1674.727)	
blocking in a:						
competitor	313.409**	0.035	281.681**	0.031	337.381**	0.306
pair	(131.686)		(127.760)		(153.278)	
complementor	-741.364	-0.009	-570.527	-0.007	-1112.410	-0.112
group	(534.132)		(498.866)		(763.320)	
complementor	-6.307	0.001	-73.379	-0.009	305.977	0.085
pair	(326.570)		(333.806)		(426.100)	
competitor	-141.859**	-0.054	-96.567**	-0.037	-102.609*	-0.365
group	(54.851)		(55.994)		(60.992)	
$\Pi_{k,t-1}$			0.873**	0.000	1.011***	5.334
			(0.234)		(0.324)	
$\Pi_{k,0}$					-0.783**	-0.247
					(0.309)	
Average market shares	1.762	-0.055	-6.308*	0.197	-7.545	-1.270
	(3.672)		(4.273)		(5.288)	
Differences in market shares	0.562	0.033	2.428	0.143	2.527	0.418
	(2.442)		(2.495)		(3.144)	
Aggregate revenues 10^{-7}	0.000	-0.116	0.000***	-0.801	0.000*	-2.506
	(0.000)		(0.028)		(0.000)	
D^N	0.157	0.157	0.025	0.025	-0.059	-0.059
	(0.127)		(0.134)		(0.161)	
D^S	-0.086	-0.086	-0.351	-0.351	-0.078	-0.078
	(0.135)		(0.154)		(0.203)	
L^p	-0.058***	-0.320	-0.065***	-0.360	-0.096***	-3.820
	(0.010)		(0.011)		(0.017)	
L^a	0.067***	0.521	0.095***	0.734	0.115***	5.492
	(0.016)		(0.018)		(0.022)	
Log-Likelihood	-360.855		-353.731		-326.875	

where ***, **, * indicate significance at the 0.01%, 0.05% and the 0.1% levels.

The descriptive statistics for this variable (Table 3) show a large part of our sample lies within the range in which the quadratic function decreases and therefore an increase in the value of an innovation reduces the probability of ex ante licensing. The elasticity of the probability of ex ante licensing with respect to changes in the expected value of an innovation at the sample mean indicates that a 10 percent increase in expected value reduces the probability of observing ex ante licensing by 8.39%. The sign of the effect is robust to our controls for unobserved heterogeneity and state dependence.

Hypothesis 2 refers to the effects on the ex ante premium of a greater blocking strength of patent portfolios for a pair of competing firms. We find that greater blocking in a *competitor pair* increases the probability of observing ex ante licensing. The variable capturing blocking in a competitor pair has a positive sign throughout and is significant at the 5 percent level.

Our results indicate that a one standard deviation increase (≈ 360%) in the expectation of the blocking strength of a rival firm's patents increases the probability that ex ante licensing is observed among product market competitors by 110 percent. These results suggest that a high blocking strength of rival firms' patent portfolios has a very strong effect on the propensity for firms to license ex ante.

Hypothesis 3 refers to effects on the ex ante premium of a greater blocking strength of patent portfolios for a group of complementors. The variable capturing blocking in a complementor group has the hypothesised sign in all specifications we report. However, the parameter is not significant at the 10 percent level. This may be due to the comparatively small number of observations for this type of contract in our sample.

The remaining interaction terms cannot be signed in our theoretical model. Our results indicate that an increase in the blocking strength of patents by 10 percent will reduce the probability of observing ex ante licensing within a competitor group by 3.6 percent. Note that this is on a par with the effect of blocking in a competitor pair, but it has the opposite sign. This effect is significant at the 5 percent level.

Overall we interpret these findings as strong evidence in favour of the validity of our theoretical model. Hypotheses 1 and 2 cannot be rejected, while the parameter for Hypothesis 3 has the correct sign. More generally the empirical model confirms that the effects of blocking in technology space on a firm's choice of licensing contract depend on whether firms are product market rivals or not.

Transaction costs Here we distinguish between the general effect of previous licensing experience and state dependence. The latter is captured by the lagged dependent variable that indicates whether a pair was engaged, in the previous period, in ex ante licensing. The test for state dependence is given by $H_0 : \rho = 0$. Our results show we can reject, at the 5 percent level, the null hypothesis that the lagged dependent variable is not significantly different from zero. The impact of state dependence is strong in comparison with the effects of the blocking strength of existing patents. If we compare two firm-pairs that differ only

in their experience of ex ante licensing in the previous period, then a pair with previous ex ante licensing experience, has a 5 percent higher probability of choosing an ex ante contract again.

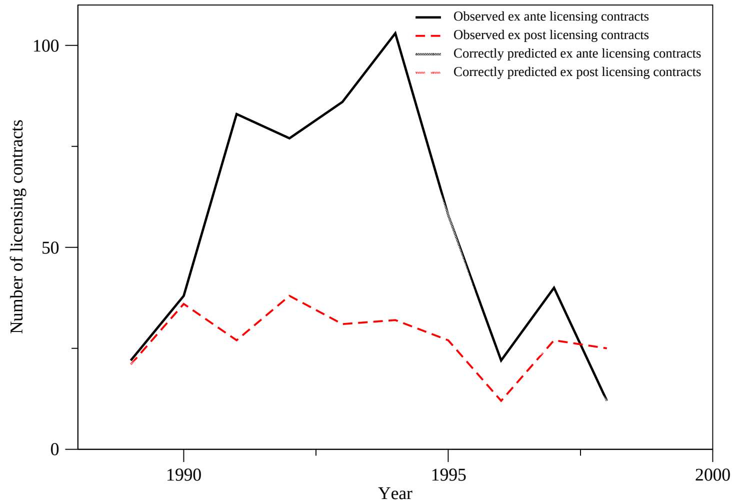
The variables counting the number of previous licensing contracts entered into by a firm-pair (L^a , L^p) are both significant at the 1 percent level in all tested specifications. We interpret this as evidence that transaction costs fall if firms have previous licensing experience. Previous experience of ex ante and ex post licensing in any period have different impact on the probability of licensing ex ante in the current period. In particular, increasing previous licensing experience by one ex ante licensing contract increases the probability of licensing ex ante in the current period by 66 percent at the sample mean. In contrast, an additional ex post licensing contract reduces the probability of licensing ex ante in the current period by 54 percent at the sample mean.

Investigating the predictive power of the model In section 2 we found licensing has developed in ways that are difficult to reconcile with the explosion of patenting in the semiconductor industry. Here we analyse whether the observed trends are due to variables which we include in our empirical model or to other unobserved variables.

To do this we plot the *correctly* predicted numbers of ex ante and ex post licensing contracts which specification (3) generates alongside the observed series in Figure 5 below.[14] The figure shows specification (3) captures the dynamics of the choice between ex ante and ex post licensing well. It is clear that this specification does better at predicting ex ante licensing.

Figure 5

Observed and correctly predicted numbers of licensing contracts in the semiconductor industry



If we focus on the relative levels of ex ante and ex post licensing contracts in the figure, then specification 3 captures both the increase in ex ante licensing between 1990 and 1994, and the decrease in ex ante licensing after 1994. Our interpretation of specification (3) above

[14] We would like to thank Jacques Mairesse for this suggestion.

showed that, *ceteris paribus*, blocking between product market competitors and previous experience of ex ante licensing are the main factors which increase the likelihood of observing ex ante licensing. This implies changes in blocking between firms that were product market rivals in this period explain the observed changes in ex ante licensing. This suggests that the observed changes in the level of ex ante licensing have come about because firms learned to avoid interactions either at the level of product market interaction or in technology space. Whether this is indeed the case is a question for future research.

Overall the results of estimating specification (3) show the choice between ex ante and ex post licensing results from a mix of strategic behaviour and firms' past licensing experience. We find that our model of licensing is supported by our empirical results. As the model is based on a patent race mechanism our model also supports the findings of Hall and Ziedonis (2001) who suggest patent thickets give rise to racing behaviour. Additionally, we find strategic behaviour resulting from racing has effects on a par with those of reductions in transaction costs.

6 Conclusion

In this paper we investigate the choice between ex ante and ex post licensing in an industry affected by a patent thicket. To accomplish this, we use a dataset comprised of semiconductor firms' licensing information which we constructed. The aim of the study is to establish how licensing affects R&D incentives in a patent thicket.

Our data show no obvious relation between patenting and licensing trends in the semiconductor industry. This is surprising given that licensing is used mainly to avoid hold-up based on blocking patents. To understand what the effects of licensing on R&D incentives are we distinguish between ex ante and ex post licensing. We find that ex ante licensing was very popular amongst semiconductor firms before 1996, thereafter its popularity rapidly declined.

To explain the observed variation in firms' choices between ex ante and ex post licensing we develop a theoretical model. This model shows the choice between ex ante and ex post licensing depends on firms' product market relationships and the extent to which they hold blocking patents. In particular, the choice of licensing contract depends on the *interaction* of these two determinants. Thus the effect of blocking on the probability of observing ex ante licensing differs, depending on whether firms are product market rivals or complementors.

We estimate a dynamic random effects probit model to test the predictions of our theory. This allows us to investigate whether there is state dependence due to a reduction in the transactions costs of a particular type of contract between two particular firms. We find strong evidence of unobserved heterogeneity and state dependence in our data. We also find evidence that past experience of a particular type of licensing contract makes it more likely that firms will choose that type of contract again. Our main findings however relate to the

hypotheses of our theoretical model. The hypotheses are supported by our empirical results. This implies changes in the choice between ex ante and ex post licensing are due to changes in firms' product market and technology space interactions. Thus stronger blocking patents lead to more ex ante licensing between product market rivals and more ex post licensing between firms that produce complementary products.

In our model we assume that firms race for stronger patent portfolios. This assumption is based on prior work by Hall and Ziedonis (2001) who argue that this is the case in the semiconductor industry. Our results are consistent with patent portfolio races between semiconductor firms. However they constitute only an indirect test as we primarily focus on how racing behaviour determines firms' licensing choices. In Siebert and von Graevenitz (2006) we derive welfare implications of choice between ex ante and ex post licensing. Racing models are often interpreted to imply that firms overinvest in R&D [Loury (1979)]. Our model implies firms avoid racing by ex ante licensing when racing would lead to very high R&D efforts; this happens when firms produce substitute products. The model also implies firms choose to enter into patent portfolio races with their complementors. Any resulting hold-up in such cases is resolved through ex post licensing. Underinvestment which characterises ex-ante agreements is likely to be particularly severe where firms are complementors. Thus patent portfolio races between such firms may be beneficial even if they lead to some overinvestment.

If our findings are supported in further research, then this implies regulation of licensing in a patent thicket is challenging. Any regulation of licensing must ensure firms' choices between ex ante and ex post licensing are not distorted. We base this conclusion on the fact that ex ante licensing contracts between complementors and ex post licensing contracts between product market rivals are likely to lower welfare. Any regulation that favours one type of licensing over the other therefore leads to welfare losses. Furthermore, we have shown that there is state dependence in firms' choices of licensing contract both within and across firm-pairs. This implies effects of regulation on earlier licensing choices will persist over time, consequently making regulation even more challenging.

Further research on how firms license therefore seems warranted. We intend to test our model of licensing in additional industries. We would also like to arrive at a better understanding of the determinants in the variation of ex ante licensing over time. Our results imply blocking between product market rivals has decreased. It is unclear whether this is due to changes in firms' patenting behaviour, their choices about product market rivalry or even coordinated changes in both dimensions. Effects of patent thickets on firms' innovation paths therefore seem to offer a promising area for further research.

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A A model of a patent portfolio race

This appendix sets out a simplified version of the model we develop in Siebert and von Graevenitz (2006) to derive the Hypotheses 1 - 3. The main results derived from this model are discussed in section 3. This appendix contains technical details of the simplified model. The main simplification consists in a functional form assumption for the R&D cost function. This leads to an analytical solution our model's second stage. We analyse the following three stage game between N firms:

Stage 1 Firms choose whether or not to license ex ante. Ex ante licensing implies that future patents protecting a valuable technology are shared.

Stage 2 Firms independently choose a hazard rate h of developing the technology and obtaining important patents to cover this technology. Their R&D costs will be increasing in the hazard rate.

Stage 3 If firms have not chosen to license ex ante, they bargain over the surplus created by the new technology. Firms' outside options depend on possession of the new patents, their complementarity to existing patent stocks C and on the blocking strength of these patent stocks B.

At stage three firms bargain over the surplus created by new patents. Bargaining arises under ex post licensing. We assume that firms achieve a solution to the bargaining problem which conforms to Nash bargaining. We model Nash bargaining between one winner and several losers of a patent race. To do this we assume that each loser has an independent opportunity to hold-up the winner of the patent race. Then the winner bargains with each loser independently over the surplus held up by that loser and the expected value of winning v_W captures the sum of the $(N-1)$ bargaining outcomes.

Under Nash bargaining the expected values of winning (v_W) and losing (v_L) the race for a new patent are:

$$v_W = \pi_W(B,C) + \frac{(N-1)}{2}\left[2\bar{\pi} - \pi_W(b,C) - \pi_L(b,C)\right] \tag{11}$$

$$v_L = \pi_L(b,C) + \frac{1}{2}\left[2\bar{\pi} - \pi_W(b,C) - \pi_L(b,C)\right] \quad , \tag{12}$$

where B is the blocking strength of existing patents and $C > B$ is the strength of the complementarity between existing patent stocks and the new patent. Then $\pi_W(B,C)$ is the expected value of disagreement with all losers for the winner of the patent race and $\pi_W(b,C)$ is the expected value of disagreement with a single loser. We define $B = (N-1)b \Rightarrow \pi_W(B,C) = \pi_W(b,C)$ if $N = 2$. The expected value of winning a patent race is decreasing in the strength of blocking patents b so that $\pi_W(b,C) > \pi_W(B,C)$ for $N > 2$.

$\pi_L(b,C)$ is the expected value of disagreement for the losers of this race. We assume that π_L is decreasing in b if firms produce substitute products and increasing in b if their products

are complements. $\bar{\pi}(C)$ is the expected value of profits if all firms have access to the new patent.

Finally we assume that all (N) firms compete in the same product market and are either all producers of substitute products or all producers of complementary products. This approach to dealing with technological rivalry between more than two firms is very simplistic but has the virtue of being tractable.

Our model of the patent race is derived from Beath et al. (1989) and Lee and Wilde (1980). The value functions for ex ante and ex post licensing in this model are:

$$V^a = \frac{(h^a + H^a)\frac{\bar{\pi}}{r} + \pi - K(h^a + r)}{h^a + H^a + r} \quad , \quad V^p = \frac{\frac{v_W}{r}h^p + \frac{v_L}{r}H^p + \pi - K(h^p + r)}{h^p + H^p + r} \quad . \tag{13}$$

where we assume that the constant $K : \frac{\bar{\pi}}{r} > K > \frac{(v_W - v_L)}{r}$, which implies that $v_L > 0$. This is a technical assumption which rules out boundary solutions to the optimisation problem.[15] π is the flow value of existing profits.

Notice that we assume only that firms will share access to the new patent under ex ante licensing. We do not assume that firms invest jointly to develop the invention that is patented. The implications of the results we derive below are robust to this modelling assumption.

The first order conditions that characterise extreme points of the value functions are:

$$\frac{[(\bar{\pi} - \pi) - KH^a]}{(h^a + H^a + r)^2} = 0 \Leftrightarrow \hat{h}^a = \frac{(\bar{\pi} - \pi)}{K(N-1)} \quad , \tag{14}$$

$$\frac{\left[\frac{(v_W - v_L)}{r}H^p + (v_W - \pi) - KH^p\right]}{(h^p + H^p + r)^2} = 0 \Leftrightarrow \hat{h}^p = \frac{r(v_W - \pi)}{(Kr - (v_W - v_L))(N-1)} \quad . \tag{15}$$

These characterise interior optima[16] and we solve for the value functions at these optima next:

$$V^a(\hat{h}^a) = \frac{N\hat{h}^a\frac{\bar{\pi}}{r} + \pi - K(\hat{h}^a + r)}{N\hat{h}^a + r} = \frac{\bar{\pi}}{r} - K \quad , \tag{16}$$

$$V^p(\hat{h}^p) = \frac{\frac{(v_W - v_L)}{r}\hat{h}^p + \frac{v_L}{r}(N\hat{h}^p + r) - (v_L - \pi) - K(\hat{h}^p + r)}{N\hat{h}^p + r} = \frac{v_W}{r} - K \quad . \tag{17}$$

The premium to ex ante licensing is defined as $\Pi = (V^a - V^p) + (T^a - T^p)$ above (eqn. (4)). The model developed here allows us to derive hypotheses about $(V^a - V^p)$. As long as the transaction costs of licensing do not vary in the same way as the expected values of licensing, we can predict whether ex ante or ex post licensing become more likely if we focus on the expected values only. We begin by deriving the sign of the difference between

[15] If we undertake comparative statics on the value of v_W, as we do below, it must be true that $\frac{\underline{\pi}}{r} > K > \frac{(\bar{v}_W - \underline{v}_L)}{r}$, where $\underline{x}$ and $\bar{x}$ indicate the lowest and highest values of a parameter x that we consider. In this sense our comparative statics results here are only local results.

[16] The second order conditions are both zero at the extreme points. However it can be shown that both derivatives are positive for values smaller than $\hat{h}$ and negative thereafter.

the expected values of licensing ex ante and ex post:

$$V^a - V^p = \frac{1}{r}\left(\bar{\pi} - v_W\right) = \frac{(N-1)}{2r}\left[\pi_L(b,C) + \pi_W(b,C) - \frac{2}{(N-1)}\pi_W(B,C)\right] - \frac{(N-2)}{r}\bar{\pi}(C) \quad . \tag{18}$$

In this simple model the expected value of ex ante licensing may be larger or smaller than that of ex post licensing. We now investigate how $(V^a - V^p)$ varies with changes in the expected value of new patents (C) and the blocking strength of firms' patent stocks (B). This leads us to the results underpinning each of our three hypotheses:

Hypothesis 1 Here we demonstrate that a stronger forward complementarity between the new patent and existing patents will reduce the probability of observing ex ante licensing.

Equation (18) can be evaluated separately for the case $N = 2$ and the case $N > 2$:

$N = 2$: This implies that $(V^a - V^p) = \frac{1}{2r}\left[\pi_L(b,C) - \pi_W(b,C)\right]$. An increase in the forward complementarity (C) will raise the expected profits of the firm winning the patent race and lower those of the losers. This implies that ex post licensing will be increasingly attractive as C increases.

$N > 2$: In this case it should be noted that $\pi_W(b,C) - \frac{2}{(N-1)}\pi_W(B,C) > 0$ and that the entire term is increasing in the forward complementarity. However the expected profit of losing the patent race is decreasing in C and the expected profits of sharing the patent $\bar{\pi}(C)$ is increasing in C. Both of these factors suggest that ex ante licensing will not be attractive as C increases for $N > 2$.

Hypothesis 2 For $N = 2$ equation (18) simplifies to:

$$(V^a - V^p) = \frac{1}{2r}\left[\pi_L(b,C) - \pi_W(b,C)\right] \quad . \tag{19}$$

An increase in the blocking strength of firms' patent stocks (B) will lower the expected value of winning a patent race $(\frac{\partial \pi_W}{\partial b} < 0)$ and increase the expected value of losing it $(\frac{\partial \pi_L}{\partial b} > 0)$. Therefore, the margin by which the expected value of ex post licensing exceeds that of ex ante licensing decreases; ex ante licensing is more likely to be observed.

Hypothesis 3 For $N > 2$ it should be noted that $\pi_W(b,C) - \frac{2}{(N-1)}\pi_W(B,C) > 0$ and that an increase in the blocking strength of firms' patent stocks b will lower the expected value of winning the patent race. Where firms produce complementary products an increase in the blocking strength of firms' patent stocks b also lowers the expected value of not winning patents (

B Data sources

This section provides details about the origin of our data on licensing, patents and market shares in the semiconductor industry.

B.1 Licensing

The basis of our data on licensing contracts was provided by Thompson Financial. We complemented this with information derived from sources in the public domain such as business reports, filings published in the National Cooperative Research Act, and announcements made in the public press.

The dataset covers licensing contracts in which at least one party has a principal line of business in the semiconductor industry between 1989-1999. All such firms for which annual semiconductor market shares were available during the period 1989-1999 were included in the sample. This sampling criterion was imposed because firms' product market positions are an important variable in our theoretical as well as statistical model. We identified name changes and subsidiaries and mergers from a variety of sources including Thomson Financial, Dataquest, and Moody's. We collect a total of 372 licensing contracts with an annual average of 34 contracts. Our data on licensing contain information on each individual contract. Details encompass the time the licensing contract was signed, the firms involved and a synopsis indicating the purpose, technology and the type of licensing, e.g. whether firms signed ex ante or ex post licensing contracts. We went through every synopsis and classified the licensing contracts into ex ante and ex post contracts. For consistency with our theoretical model our empirical analysis of licensing is retsricted to horizontal technology licensing. Hence, we have excluded vertical partnerships, such as those between semiconductor firms and computer, microelectronic or multimedia firms. In line with the previous literature we classified a licensing contract as horizontal if more than 50% of the firms had sales in the semiconductor industry. We also excluded contracts that were based exclusively on production and marketing licensing. Finally, we dropped another 22 licensing contracts which were related to litigation. This left us with 579 contracts over the whole time span.

The number of licensing contracts we observe is in line with that reported by Rowley et al. (2000) for an overlapping sample period. Their data derives from different data sources than ours.[17] The correspondence in the number of contracts observed confirms that our dataset contains a comprehensive record of information on licensing available in the public domain. As Anand and Khanna (2000) note there is no requirement for firms to publish information on licensing contracts. Therefore it is conceivable that some bias due to sample selection remains. However we are unaware of reasons for which firms should selectively favour ex

[17] Rowley et al. (2000) study strategic alliances whereas we study licensing contracts. Our definition of a licensing contract is any contract that also includes an agreement to license technology. Therefore both studies focus on a similar set of agreements between firms.

ante or ex post licensing contracts when announcing licensing contracts to the public.

B.2 Patents

In order to capture firms' positions in technology space we use information on granted patents.[18] We use U.S. domestic patents in our study because the U.S. is the world's largest technology marketplace and it has become routine for non-U.S.-based firms to patent in the U.S. [Albert et al. (1991)]. Our data on granted patents are taken from the NBER patent dataset established by Hall, Jaffe, and Trajtenberg (2001).[19] The database comprises detailed information on 3 million U.S. patents granted between 1963 and 1999, and all citations made between 1975 and 1999 (more than 16 million).

A major challenge in any study that examines the patenting activities of firms over time is to identify which patents are assigned to individual firms in a given year. Firms may patent under a variety of different firm names over time. To retrieve patent portfolios of the firms we follow the same procedure as Hall and Ziedonis (2001). This procedure was also used for our licensing data.

Using the patent database we extract detailed patent information for every semiconductor firm for our sample period 1989-1999. We use the number of annual granted patents, patent stocks (accumulated patents) dating back to 1963, as well as patent citations dating back to 1975. Moreover, in order to establish firms' position in technology space at a disaggregated level, we make use of information about the technology area that the filed invention belongs to. The USPTO has developed a highly elaborate classification system for the technologies to which the patented inventions belong consisting of about 400 main 3-digit patent classes. Each patent is assigned to an original classification. We chose 9 out of the 400 patent classes that are connected to memory chips, microcomponents and other semiconductor devices.

As the patent database lasts only until 1999 we need to take truncation of the data into account. Therefore, our patent based variables are based on annual patent shares. Throughout we divide the number of firms' patents and citations by the total number of patents and citations of all semiconductor firms in a given year.

B.3 Market data

Annual semiconductor market data at the firm-level were provided by Gartner Group. All merchant firms were tracked whose annual sales exceed $10 million a year. Thus, we cover approximately the whole population of semiconductor firms and do not need to rely on business sheet information to infer market shares. On average, there are 155 companies present in the market every year. Approximately 60% of the firms had their headquarters in the U.S.,

[18] By filing a patent an inventor discloses to the public a novel, useful, and non obvious invention. If the patent gets granted, the inventor receives the right to exclude others from using that patented invention for a certain time period, which is 20 years in the U.S.

[19] Further information about the database can be found at http://www.nber.org/patents/.

whereas the rest were located in Japan, Europe, and other Asian countries. Again, we correct for mergers and acquisitions that were announced in the above mentioned sources.

We are able to separate the semiconductor market share into three different market segments: memory chips, microcomponents, and other devices. Based on this classification we are able to distinguish whether firms produce substitute or complementary products. If two firms have positive market shares in the same segment at least once, we consider them to be producing substitute products, and complementary products otherwise.

C Examples for ex ante and ex post licensing

This section contains examples of licensing contracts taken from our dataset.

EX ANTE LICENSING

- Texas Instruments and NEC Corp entered into a ten-year cross-licensing agreement to patent semiconductors. Under the terms of the agreement, the two companies were to have use of each others patents involved in manufacturing semiconductors. Date: 06/12/1997.
- Sony Corp and Oki Electric Industry Corp entered into an agreement to jointly develop a 0.25 micron semiconductor manufacturing process. Under the terms of the agreement, Oki was to use the technology for 256 Mbit “Dynamic Random Access Memory”, while Sony was to produce logic integrated circuits (IC’s) for home electronics and AV equipment. Financial terms were not disclosed. Date: 20/11/1995.

EX POST LICENSING

- Ramtron International Corp, a unit of Ramtron Holdings Ltd, and International Business Machines Corp(IBM) signed a manufacturing and licensing agreement in which Ramtron was to grant IBM the rights to manufacture and market the Ramtron EDRAM dynamic random access memory chip. Under the terms of the agreement, IBM was to supply Ramtron with EDRAM chips. The EDRAM chips were to be manufactured at IBM’s facility in Essex Junction, VT. No financial details were disclosed. Date: 05/08/1995.
- Compaq Computer Corp and Cyrix Corp entered into an agreement which stated that Cyrix Corp granted Compaq Computer a license to manufacture Cyrix Corp’s M1 microprocessor chips. The agreement stated that production of the M1 microprocessor chips in the first quarter of 1995. Financial terms of the agreement were not disclosed. Date: 05/10/1994.