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

Ralph Siebert (Purdue University and CEPR)*
Georg von Graevenitz (University of Munich)†

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Abstract

We study licensing in a high technology industry affected by a patent thicket. Licensing contracts signed with rival innovators allow firms to contain the threat of hold-up that arises in the patent thicket. Licensing contracts will have very different effects on firms' R&D incentives depending on when they are signed. Therefore we distinguish between ex-ante and ex-post licensing contracts which are signed before or after R&D investments are made. We find that there is considerable variation in firms' choices between these forms of licensing. To explain this variation we develop an empirical model that nests transactions costs, technology and product market determinants of the choice of licensing. This model is tested employing a dynamic binary choice model with unobserved heterogeneity, strictly exogenous variables as well as a lagged dependent variable. The initial conditions problem is dealt with according to a method suggested by Wooldridge (2005). We estimate a random effects probit model using conditional ML and find evidence of state dependence in our model. The predictions of our empirical model are confirmed. In particular we find that ex-ante and ex-post licensing resolve different forms of hold-up and derive implications for the regulation of licensing in the industry we study.

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*Ralph Siebert, Purdue University, Department of Economics, Krannert School of Management, 403 West State Street, West Lafayette, IN 47907-2056, rsiebert@purdue.org.

†Georg von Graevenitz, graevenitz@bwl.uni-muenchen.de, INNO-tec, Munich School of Management, Kaulbachstraße 45, $D - 80539$, Munich.

1 Introduction

The modern process of research and development is sometimes likened to the activity of continuously extending a pyramid by placing new blocks on top of existing ones. Here the pyramid serves as a metaphor for the cumulativeness of scientific research in complex product industries[1]. Inventions are invariably based on the results of earlier research.

In many high technology industries the cumulativeness of research efforts is reflected in a dense web of interconnected intellectual property rights - a patent thicket [Shapiro (2001)]. Whenever a firm successfully places a new block on top of the pyramid the value of this block to that firm will not just depend on the height of the block itself, i.e. the advance it embodies. It will also depend on the extent to which the block rests on foundations which belong to rival firms. The more the foundations of a new innovation belong to rivals, the greater the royalties which these will extract from the owner of that innovation. This ability of previous innovators to extract royalties is sometimes described as their ability to hold-up follow on innovators by employing their own patents as blocking patents [2].

In order to contain the threat of hold-up firms employ an array of strategies. One important strategy is strategic patenting of large numbers of patents. By patenting heavily firms acquire large patent portfolios; the patents in these portfolios serve as bargaining chips. These have two functions: they allow the firms to bargain for access to the proprietary technology of their competitors and they enable them to threaten with a countersuit if they are held-up. Ziedonis (2004) provides evidence of defensive patenting in the semiconductor industry. She shows that semiconductor firms responded to a more fragmented ownership of patents complementary to their own, by patenting more aggressively. Here greater fragmentation of ownership signals greater need to bargain for access to intellectual property rights. In an earlier study Hall and Ziedonis (2001) document the rise of defensive patenting in the semiconductor industry after 1985.

Once firms are part of the race to acquire substantial patent portfolios they must deal with the problem of potential hold-up situations. The obvious way of dealing with hold-up is through cooperation with rival innovators. Cross-licensing agreements between rival innovators that resolve mutual hold-up situations are very common in industries affected by the patent thicket [Grindley and Teece (1997); Anand and Khanna (2000)]. Such cross-licensing agreements may apply to existing patent portfolios, but may also be forward looking [Shapiro (2001)]. Alternatively firms may cooperate on entire R&D projects through the formation of Research Joint Ventures (RJVs). Ex-ante R&D cooperation of this kind may allow firms to prevent hold-up from arising at all.

In this paper we investigate licensing as a response to the threat of hold-up within the patent thicket. Licensing is almost always part of the strategy of resolving hold-up, even if firms have also established more formal ties in the form of RJVs[3]. The study of licensing

[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] The hold-up problem is discussed at length by Shapiro (2001). Hall and Ziedonis (2001); Hall (2004) argue that the Kodak-Polaroid case of 1985-1986 first demonstrated how damaging a patent infringement suit could become for semiconductor firms. The potential for aggressive use of patents was also underlined when Texas Instruments started using their patent portfolio to sue Japanese and U.S. rivals for patent infringement [Grindley and Teece (1997)].

[3] In the literature on R&D cooperation it is more common to focus on the question whether firms cooperate or not [Stuart (1998); Sakakibara and Branstetter (2002); Sakakibara (2002); Cassiman and Veugelers (2002); Hernán et al. (2003); Röller et al. (2005)]. Oxley (1997) adopts a transactions costs approach to R&D cooper-

behaviour within the patent thicket is important for at least two reasons: firstly it is hypothesised that the threat of hold-up may dull R&D incentives [Shapiro (2001)] and secondly it is feared that cross-licensing contracts may be used to establish collusive agreements [Shapiro (2003a)]. We focus on the first of these issues and seek to establish how licensing will affect R&D incentives when firms anticipate hold-up by rivals.

To investigate the effects of licensing on R&D incentives we introduce the distinction between ex-ante licensing and ex-post licensing. Economic theory suggests that ex-ante licensing will lead to lower research efforts than ex-post licensing. We develop a latent variable model of the premium to ex-ante licensing and study the choice between ex-ante and ex-post licensing using a dynamic panel data model. Our empirical model draws on a theoretical model of licensing under the shadow of hold-up [von Graevenitz and Siebert (2005)] . We integrate their theoretical predictions in a dynamic empirical model which also incorporates effects of experience with licensing from previous periods. In this model it is possible to distinguish between experience gained in all previous licensing ventures and experience that is specific to a firm pair.

We seek to derive two results that are relevant to policy making. Firstly we hope to establish how important state dependence is when firms choose the form of licensing contract. If state dependence is particularly strong this implies that any policies which favour a particular type of contract may have stronger effects than anticipated because firms become locked into this type of contract. Secondly we hope to find support for the theoretical model developed by von Graevenitz and Siebert (2005). This model shows that firms are more likely to choose ex-ante licensing if they are competitors in the product market and ex-post licensing if they produce complementary products. A welfare analysis of the model implies that firms are unlikely to choose contracts that reduce welfare. If we can support the theoretical model this suggests that the regulation of licensing contracts should seek to be neutral in its effects on the choice between ex-ante and ex-post licensing.

We test the predictions of the theoretical model using a dataset containing licensing contracts from the semiconductor industry. This industry is a natural choice for an empirical study of hold-up because of its overall economic significance[4] and because there is a growing body of literature which documents the emergence of the patent thicket in this industry[5]. While it is clear that the growing patent thicket has contributed to an increase in the propensity of semiconductor firms to cooperate on R&D [Stuart (1998)], there is no previous work on the choice between ex-ante and ex-post licensing in this industry or any other. We provide empirical evidence on the determinants of this choice. We find that there was a particularly strong increase of the propensity to engage in ex-ante licensing over the first part of our sample. Subsequently there was an equally strong decline of the propensity to cooperate ex-ante. We also document that ex-ante licensing was far more likely to be observed than ex-post licensing.

To investigate the choice between ex-ante and ex-post licensing we estimate a dynamic probit model allowing for unobserved heterogeneity. The econometric task we face is to distinguish state dependence from dynamic responses to exogenous variables caused by unobserved heterogeneity and serial correlation. We allow for lagged dependent and lagged exogenous variables in order to accurately test for state dependence. We also allow for unobserved heterogeneity as firms may differ in certain unmeasured variables that influence

ation and focuses on the strength of the cooperative contract. Our paper ignores the question of the strength of the overall agreement and focuses on the licensing element which is common to almost all R&D cooperation.

[4]Jorgenson (2001)

[5]Grindley and Teece (1997),Shapiro (2001),Hall and Ziedonis (2001),Ziedonis (2003)

their choices between ex-ante and ex-post licensing. If these unobserved variables are correlated over time and are not properly controlled for, 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 needs to account for unobserved heterogeneity and other sources of serial correlation in unobservables. [Wooldridge (2005)] shows how this may be done and we apply the method he suggests below.

State dependence will arise where experience accumulated in previous licensing between two partner firms affects their current choices to cooperate on R&D. Previous cooperative R&D agreements will also have an impact on firms' current positions in technology space, which then affects current expected profits from licensing. The empirical literature on R&D cooperation documents the importance of previous experience of cooperation in determining firms' propensity to cooperate again [Hernán et al. (2003),Sakakibara (2002),Stuart (1998)]. Therefore we expect that state dependence will be an important determinant of the choice between ex-ante and ex-post licensing.

In nonlinear dynamic panel data models with unobserved effects, the treatment of the initial 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 different ways to handle the initial conditions problem in parametric dynamic nonlinear models are suggested by [Hsiao (1986)]. Here we use the method suggested by Wooldridge (2005) to handle the initial conditions problem. 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. Then we integrate out the unobserved heterogeneity of the joint density. We estimate a random effects probit model using conditional ML.

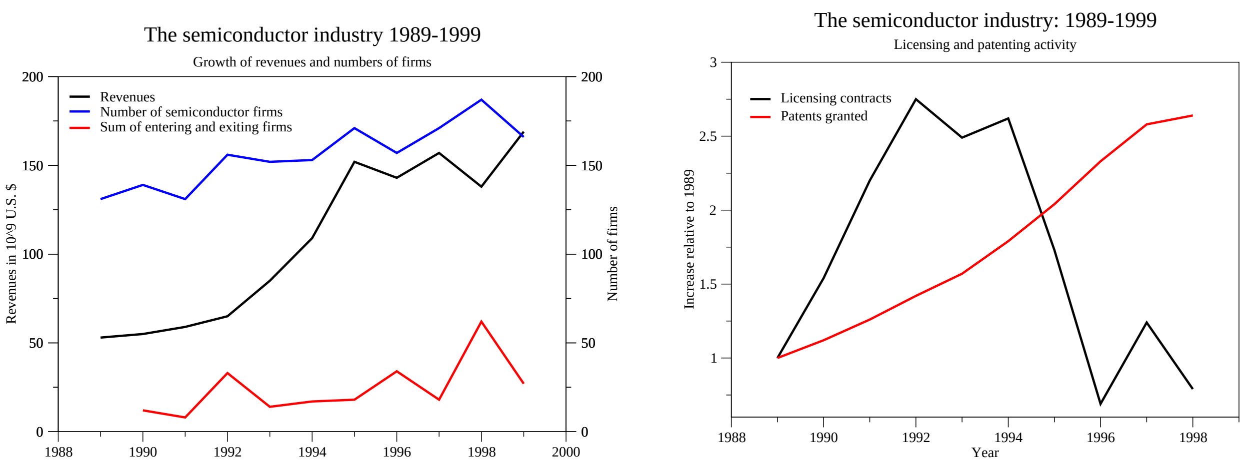
Our paper is organised as follows: in section 2 we provide an exploratory account of licensing in the semiconductor industry, then in section 3 we introduce our analytical framework. In the following section we discuss our specification. In section 5 we discuss the results. Finally section 6 concludes. In the appendix we provide more information on our dataset as well as additional results of alternative specifications.

2 Licensing in the semiconductor industry

In this paper we study licensing between semiconductor firms empirically. We construct a dataset which covers the period 1998-1999. It comprises 1171 records of licensing amongst semiconductor firms. Furthermore it contains information on semiconductor firms' revenues and market shares and their patenting activity. In this section we describe the most important empirical patterns which characterise licensing in the semiconductor industry using this dataset.

The semiconductor industry has been a driver of economic growth for more than a decade. Jorgenson (2001) argues that the semiconductor industry is one of the most important high-technology industries, as its prices significantly affect many other downstream industries. Semiconductors are mainly used as inputs for the computer industry (45% of its sales), consumer electronics (23%), and communications equipment (13%). Anand and Khanna (2000), who undertake a first large sample study of licensing, find that the semiconductor industry emerges as one of the industries with the highest levels of licensing activity. Therefore this is a natural setting in which to study licensing. Furthermore 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)]. Our aim is therefore to understand how the emerging patent thicket has affected licensing activity in the semiconductor industry. The descriptive statistics which we present in this section contain some surprising facts about licensing amongst semiconductor firms. We begin by focusing on these facts and then go on to discuss the origin of the data we use in more detail.

The left-hand graph in Figure 1 shows that total revenues of all semiconductor firms grew very substantially over the period of our sample. Mirroring this there was also a large increase in the number of active semiconductor firms. However the graph also demonstrates that revenue growth almost stopped after 1996. After this date there was 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.

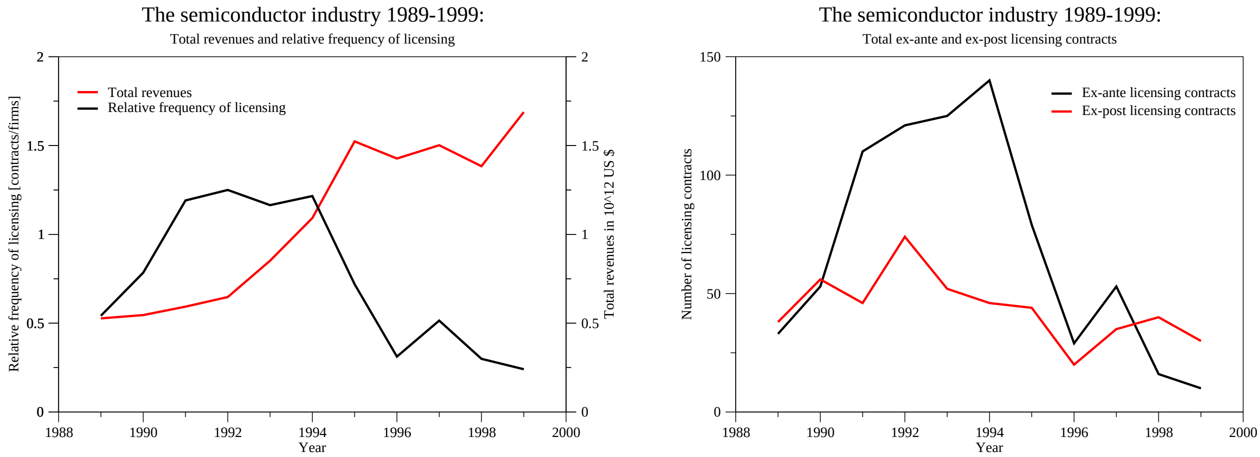


Source: These figures are based on tables 5 and 6 in the appendix.

Figure 1: The development of the semiconductor industry 1989-1999

The semiconductor industry experienced a strong surge in patenting activity after 1985 [Hall and Ziedonis (2001), Ziedonis (2003, 2004)]. The right-hand graph of Figure 1 provides information on the level of granted patents and licensing contracts relative to 1989. It shows that 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 the right-hand graph of Figure 1 shows the number of licensing contracts amongst semiconductor firms in our sample increases and decreases in a fashion that shows no obvious relation to the increase in granted patents.

If we combine the information about revenues and licensing activity contained in the two graphs of Figure 1 in one graph a possible explanation for the rapid decline of licensing just before 1996 emerges: expected revenue growth may have had some impact on the level of licensing activity. This is documented in the left hand graph of Figure 2 below. The figure contains plots of the total revenue of all semiconductor firms and of the frequency of licensing contracts relative to the number of firms in the semiconductor industry. The relative frequency of licensing contracts displays a hump shape just as the absolute number of licensing contracts does. The graph also illustrates that between 1991 and 1994 the number of licensing contracts was greater than the number of semiconductor firms. The decline in licensing activity begins about a year before total revenues stopped growing. This suggests that firms anticipated the decline in revenue growth and reduced their licensing activities accordingly.



Source: These figures are based on tables 5 and 6 in the appendix.

Figure 2: Ex-ante and ex-post licensing contracts in the semiconductor industry

Our data on licensing contain some information on each individual contract [6]. This information allows us to distinguish between licensing contracts that were signed before R&D investments took place (ex-ante contracts) and those signed after such investments had turned into granted patents (ex-post contracts). The right hand graph above shows that ex-ante licensing is far more volatile over the period of our sample than ex-post licensing. This finding is somewhat surprising as the literature on patent thickets has focused on ex-post cross licensing or the formation of patent pools as a means of resolving the threat of hold-up [Grindley and Teece (1997), Shapiro (2001)] so far. In sum Figure 2 shows clearly that the increase in overall licensing is predominantly a result of the strong increase in ex-ante licensing over the period of our sample.

Our data show ex-post licensing is important throughout the period, but it is dwarfed by the level of ex-ante licensing before 1996. To gain a better understanding of what underlies the patterns of ex-ante and ex-post licensing illustrated in Figure 2 we collect information on the top 20 firms by granted patents 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 a given type which each firm was a party to.

Table 1 shows that Texas Instruments and Intel account for a fifth of all ex-post licensing agreements[7]. This may explain why previous studies highlight ex-post licensing as these have tended to focus on these firms [Grindley and Teece (1997),Shapiro (2001),Shapiro (2003b)]. By comparison the number of ex-ante licensing agreements is spread quite evenly across the firms represented in the table. In spite of this difference between ex-ante and ex-post

[6] We provide examples of such contract descriptions in Appendix B below.

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

licensing it is clear that all of the represented firms engage in both types of licensing to a significant degree.

Overall we observe that 29% of the contracts in our sample are signed by firms which have experience of both ex-ante and ex-post licensing. Therefore we cannot explain the patterns observed above by focusing only on firms that tend to choose one form of licensing contract only, rather we must focus on the choice that all firm pairs make between ex-ante and ex-post licensing.

In Table 1 we highlight the three most important firms in each column:

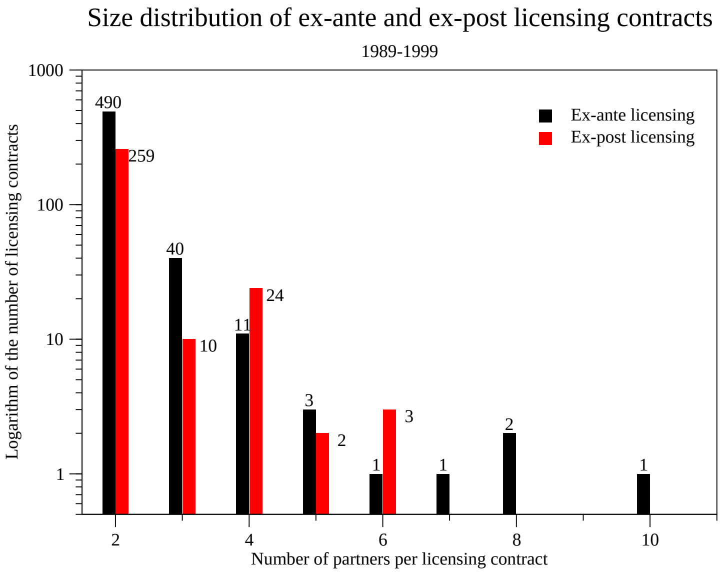
Table 1: Licensing by the largest semiconductor firms 1989-1999

Company	Patents	Revenues	Av. Mkt. shares (%)	Percentage of total lic.	Percent. of ex-ante lic.	Percent. of ex-post lic.
IBM	**3802**	21,909	1.85	**5.55**	**6.92**	3.02
NEC	**3072**	**81,677**	**6.91**	3.66	4.19	2.68
TOSHIBA	**3041**	**69,974**	**5.92**	4.84	**5.46**	3.69
SONY	2343	17,690	1.50	2.01	2.00	2.01
FUJITSU	1894	40,520	3.43	3.42	3.28	3.69
TEXAS INST.	1837	56,006	4.74	**8.74**	**5.46**	**14.77**
MICRON TECH.	1746	15,836	1.34	1.06	0.73	1.68
MOTOROLA	1739	66,700	5.65	5.31	**6.56**	3.02
SAMSUNG	1645	46,344	3.92	2.95	2.55	3.69
MATSUSHITA	1367	28,021	2.37	2.24	2.19	2.35
AMD	1085	20,725	1.75	2.48	1.64	4.03
S.G.S. THOMSON	994	17,991	1.52	1.89	2.19	2.34
INTEL	938	**135,069**	**11.43**	**5.67**	4.74	**7.38**
UNITED MICRO.	776	3,108	0.26	0.24	0	0.67
NAT. SEMI. CORP.	639	22,571	1.91	3.90	3.46	**4.70**
HYUNDAI EL.	590	18,450	1.56	0.83	0.36	1.68
LG CABLE & MACH.	546	8,445	0.71	0.47	0.73	0
LSI LOGIC CORP.	453	11,335	0.96	2.60	1.82	4.03
AT & T	431	5,531	0.47	2.36	2,55	2,01
OKI ELECTRIC IND.	370	12,872	1.09	1.89	1.82	2.01
Industry total		1,181,420		100%=847	100%=549	100%=298

Revenues are stated in millions of 1989 $\$'s$.

In summary the data we have studied so far suggest that there are significant differences between ex-ante and ex-post licensing by semiconductor firms. Furthermore the data reveal changes in the level of licensing that do not look as if they arise solely from the development of total industry revenues or patenting behaviour. The remainder of the paper sets out a model that seeks to explain how semiconductor firms choose between ex-ante and ex-post licensing. We test this model using the dataset described here.

This dataset provides one further stylised fact which we use in our analysis below. As the histogram in Figure 2 illustrates, the vast majority of the contracts we observe are bilateral. Nonetheless a significant proportion (11.6%) of the contracts in our sample are between more than two firms. Due to this fact we also develop hypotheses that pertain to these types of contracts.



Our data derive from a variety of sources. Here we discuss the sources of the data and their quality:

Licensing The data on licensing contracts were originally taken from Thompson Financial. We have complemented these with information derived from further sources that are in the public domain such as business reports, Lexis/Nexis, Electronic News, Electronic Business etc . We restrict our empirical analysis of licensing to the formation of horizontal technology licensing, thereby excluding licensing for production and marketing. Hence, we have excluded vertical partnerships, such as those between semiconductor firms and computer or microelectronic or multimedia firms. Moreover we have excluded 22 ex-post licensing deals, which were related to infringements and lawsuits.

We believe that this dataset provides at least as much information on licensing activities in the semiconductor industry as datasets obtained by previous studies. The number of 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[8]. 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-ante or ex-post licensing contracts when deciding which to announce.

Patents Information on granted patents comes from the NBER patent dataset[9]. We extract all inventions that have been patented in the U.S between 1989 and 1999. We use domestic patents 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)].

[8]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

[9]This dataset is described at http://www.nber.org/patents/. It was established by Hall et al. (2001).

Market data Data on annual sales and market share data come from Gartner Group...

This completes our survey of the descriptive evidence on licensing in the semiconductor industry. We turn now to the analytical framework which we use to investigate the choice between ex-ante and ex-post licensing.

3 An empirical model of licensing

In this section we develop an empirical model to study the choice between ex-ante and ex-post licensing. Here we begin by discussing the theoretical background for such a model.

Hall and Ziedonis (2001) demonstrate that patent portfolio races between semiconductor firms are giving rise to a patent thicket. Hold-up opportunities arise naturally in this context and ex-post licensing allows firms to resolve such hold-up situations. Where the possibility of hold-up can be anticipated firms also have the option of licensing ex-ante. Ex-ante licensing contracts allow firms to avoid races for particular patents by agreeing some form of sharing of the costs and benefits of these patents. The distinction between ex-ante and ex-post licensing arises naturally when patent portfolio races are considered in this way. Indeed Ziedonis (2004) shows that ex-ante licensing will be less likely where ownership of complementary patents is very fragmented. The result is that greater fragmentation leads to more intense patent portfolio races and more ex-post licensing. While Ziedonis (2004) considers the indirect consequences of the choice between ex-ante and ex-post licensing we are able to observe the choice directly.

In von Graevenitz and Siebert (2005)(*vGS*) we model the choice between ex-ante and ex-post licensing as a choice between ex-ante licensing and entry into a patent race. Where firms opt for the patent race they will subsequently bargain over the surplus created by the new patent. The necessity for such bargaining is the result of the complementarity between the new patent and existing patents. By incorporating this complementarity our model extends previous models of patent races in a tractable fashion. In particular we build on the work of Beath et al. (1989) and Nti (1997) to derive comparative statics results about the implications of exogenous variation in the strength of existing blocking patents and the value of new patents.

The literature on patent races discussed by Beath et al. (1989) and Reinganum (1989) makes strong predictions about R&D investment by losing firms. These predictions are not confirmed in a detailed empirical study of R&D investment behaviour in the pharmaceuticals industry by Cockburn and Henderson (1994). They conclude by arguing that more realistic models of R&D competition should allow for patent races that offer multiple prizes. Recent work that seeks to meet this challenge includes Hörner (2004) and Konrad and Kovenock (2005). The work of Hall and Ziedonis (2001) and Ziedonis (2004) suggests that patent race models have some application to complex product industries, such as the semiconductor industry, too. However the obvious challenge there is to extend the models to incorporate complementarities between patents. Our theoretical model in *vGS* represents an attempt in this direction.

In an earlier study of cross-licensing of complementary technologies Fershtman and Kamien (1992) model a simultaneous race for two technologies by duopolists. In their model an R&D race is followed by bargaining over the surplus that may be created when firms cross-license their innovations. Their model is too complex to provide the comparative statics results we seek. Therefore in *vGS* we study a race between N firms for a single new patent. This simpler setting is rich enough to generate opportunities for cross-licensing because we allow for the possibility that the future owner of the patent may be held-up by one or more losers of the R&D race. Hold-up arises because of the complementarity of the new patent to existing patents. Ex-post cross-licensing resolves hold-up by providing the loser(s) of the R&D race access to the new patent while providing the winner access to the blocking patents of the losing firms. We allow for the possibility that firms anticipate the patent race and contract ex-ante to avoid it. Here we assume that firms are sufficiently forward looking to trade off ex-ante and ex-post licensing[10].

In our theoretical model firms' strategic R&D incentives differ under ex-ante and ex-post licensing. We find that firms' R&D incentives are much greater under ex-post licensing than under ex-ante licensing. Ex-post licensing takes place as soon as a firm owns a valuable new patent. This implies a prior race for ownership of that patent. Ex-ante licensing will take place before any R&D investment and firms will contract to share future discoveries[11]. This reduces R&D investment in patents covered by an ex-ante licensing contract.

In the remainder of this section we develop an empirical framework within which the predictions of our theoretical model may be tested.

3.1 A latent variable model of the premium to ex-ante licensing

In this section we set out a latent variable model of the choice between ex-ante and ex-post licensing. The unobserved premium to ex- ante licensing for the firm pair k at time t may be regarded as a latent variable $\Pi^*_{k,t}$:

$$\Pi^*_{k,t} = \left(V^a_{k,t} - V^p_{k,t}\right) + \left(T^a_{k,t} - T^p_{k,t}\right) + u_{k,t} \ , \tag{1}$$

where V^a, V^p are the expected values of ex-**a**nte and ex-**p**ost licensing, T^a, T^p are the transactions costs associated with ex-ante and ex-post licensing and $u_{k,t}$ is a continuously distributed error term with mean zero.

The premium to ex-ante licensing is a function of transactions costs differences between ex-ante and ex-post licensing as well as the determinants of the expected values of ex-ante and ex-post licensing. The premium may be positive or negative - in the former case we observe ex-ante licensing and in the latter ex-post licensing.

This simple model allows for both transactions costs effects and effects deriving from strategic behaviour of technological rivals. In order to estimate the model it would be desirable to have structural expressions for V^a, V^p, T^a, T^p. While there is a theoretical model that provides the value functions V^a, V^p and we have enough data to test this model, we do not have sufficient data to test a theoretical model of T^a, T^p. Furthermore the value functions for V^a, V^p that *vGS* derive are non-linear in our explanatory variables. Therefore we approximate the difference $(V^a - V^p)$ with a linear model on which we impose the comparative statics properties of the original value functions. We combine this model with proxies for the transactions costs of ex-ante and ex-post licensing.

We discuss the components of the approximated linear version of equation (1) next.

The expected values of licensing ex-ante and ex-post (V^a, V^p) *vGS* model the setting of technological rivalry and licensing described above. In Appendix A we provide an example

[10] Recent survey evidence from a study of European inventors [Gambardella et al. (2005)] suggests that almost three quarters of all inventions covered there were the result of forward looking R&D investment as opposed to luck or ...

[11] Compare the texts describing the licensing contracts between xand y in appendix B.

of their model and derive the main predictions discussed below. *vGS* assume that transactions costs are independent of the determinants of the expected values of ex-ante and ex-post licensing and concentrate on the latter. They analyse a three stage game between N firms:

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

Stage 2 Firms independently choose a hazard rate h of patenting an important new innovation. Their R&D costs will be increasing in the hazard rate.

At the end of this stage the patent is granted to one of the firms.

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

In this setting the strength of R&D incentives at stage 2 depends on the form of contract chosen. Ex-ante cooperation removes the threat that a rival firm will raise its profits while lowering own profits. Beath et al. (1989) call this the *competitive threat*. The remaining R&D incentive in this case is the *profit incentive* which arises because the new patent improves all firms' profitability. Under ex-post licensing both of these incentives determine the level of R&D investment and therefore it will exceed investment under ex-ante licensing.

The greater costs of R&D rivalry under ex-post licensing are compensated by higher profits for the firm winning the new patent. As a result firms face a choice between ex-ante and ex-post licensing. This choice is influenced by the value of the prize which the winning firm gains under ex-post licensing. On the basis of comparative statics results derived by Nti (1997) it is possible to show that the expected values of ex-ante and ex-post licensing are increasing in the prize. *vGS* show that initially the expected value of ex-post licensing grows faster than that of ex-ante licensing. For very large prizes this result is reversed.

The prize will grow in value if the new patent is a stronger complement to existing patent stocks. This forward complementarity is measured by C. It will also grow if the value of the products which the patent improves is greater. We represent this value by W. The relationship between the value of the prize and these parameters is captured by the following hypothesis:

Hypothesis 1
The relationship between the probability of observing ex-ante licensing and an increase in the value of a new patent is U-shaped . For new patents of low value such increases will reduce the probability of observing ex-ante licensing. For very valuable new patents such increases raise the probability of observing ex-ante licensing.

This hypothesis follows from well-known comparative statics properties of standard patent race models[12]. It can be represented as follows:

$$V^a - V^p = \gamma_1 CW + \gamma_2 (CW)^2 \qquad , \tag{2}$$

where γ_1, γ_2 are parameters to be estimated. Hypothesis 1 suggests that $\gamma_1 < 0$ and $\gamma_2 > 0$.

Now consider the effects of variation in the blocking strength of existing patent stocks B.

[12] For discussions of the comparative statics of patent race models refer to Reinganum (1989), Beath et al. (1994) or Nti (1997).

The blocking strength of existing patent stocks is irrelevant under ex-ante licensing if the firms are symmetrical. Symmetry implies that each firm is equally well placed to hold-up the use of a new patent by the other. Ex-ante licensing prevents hold-up, through the provision that a firm which gains the new patent will share it with the partners to the contract. In contrast ex-post licensing occurs because the firm holding the new patent desires to resolve the hold-up problem. Its contracting partners may wish to use the new patent too. In this bargaining setting the size of the "pie" which bargaining is over will depend on the blocking strength of existing patent stocks. As the pie is divided between the winner and loser(s) of the patent race, both sides' payoffs also depend on the blocking strength of existing patent stocks. Thus the prize being offered in the patent race is a function of this exogenous parameter.

The comparative statics results which *vGS* derive regarding the effects of B depend delicately on the number of contracting parties N and on the product market relation between the contracting parties. The simplest case is that of two firms which are product market rivals.

In this case a higher ability to block the new patent will lower the value of winning the patent. There is a direct effect which lowers the outside option of the winning firm. Indirectly a greater ability to block the patent increases the pie which winner and loser bargain over ex-post. However *vGS* show that this indirect effect does not compensate the direct effect.Therefore we advance the following hypothesis:

Hypothesis 2
If exactly two firms contract and these compete in the product market, (substitute products) we find that stronger blocking patents reduce the expected value of ex-post licensing. This implies that ex-ante licensing becomes more likely.

A more complex case arises where firms produce complementary products. Complementarity in the product market implies that one firm's profits are increasing if its partners become more competitive. As a consequence the owner of a new patent that is valuable 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. Just as before an increase in the blocking strength of existing patents will lower the outside option of the winning firm. However *vGS* show that the indirect effect which arises from the growth of the bargaining pie will more than compensate the direct effect as soon as more than two firms contract over the new patent ex-post. Therefore we advance a third hypothesis:

Hypothesis 3
For patent races with more than two competitors the expected value of ex-post licensing increases in the strength of blocking patents where firms produce complementary products. This implies that ex-post licensing becomes more likely.

The last two hypotheses depend on the values of B, N 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. Because of data limitations we also introduce a dummy variable which captures whether firms produce substitute products $(D_S = 1)$ or not. With the help of these dummy variables we capture Hypotheses 2 and 3 as follows:

$$V^a - V^p = \gamma_3 B(1 - D_N)D_S + \gamma_4 B D_N(1 - D_S) + \gamma_5 B(1 - D_N)(1 - D_S) + \gamma_6 D_N D_S \quad , \tag{3}$$

where the parameters $\gamma_3 - \gamma_6$ remain to be estimated. Hypothesis 2 and 3 suggest that $\gamma_3 > 0$ and that $\gamma_4 < 0$. We cannot derive restrictions on the signs of γ_5 and γ_6. If the signs of these parameters are positive this suggests that the direct effect discussed above outweighs the indirect effect.

This completes our discussion of the linear approximation of $V^a - V^p$). We turn to consider the effects and measurement of transactions costs next.

Transactions costs (T^a, T^p) As the latent variable model set out above suggests the transactions costs associated with ex-ante and ex-post licensing may be significant. We assume that previous experience of either type of R&D cooperation reduces the transactions costs of later licensing of the same type. Then the transactions costs of ex-ante and ex-post licensing are decreasing functions of the total number of previous ex-ante and ex-post R&D agreements (L^a, L^p) which each firm has entered into. The previous empirical literature on R&D cooperation has shown that the probability of R&D cooperation increases in the amount of earlier cooperation which two firms have undertaken[13]. Oxley (1997) finds that previous experience of cooperation does not predict the hierarchical form of R&D cooperation which firms adopt. Nonetheless we conjecture that previous experience of each type of licensing will reduce the transactions costs associated with that form of cooperation. L^a, L^p are employed as proxy variables for transactions costs below.

A further observable dimension of transactions costs are relationship specific transactions costs. By the same logic as above we hypothesise that previous experience of contracting with a specific firm will reduce costs of transacting with that firm, in the same way, again. Therefore we consider the possibility of state dependence.

Approximating Π Combining the terms derived in the preceding paragraphs into a single expression, we derive the linear approximation to the latent variable model of equation 1:

$$\Pi^*_{k,t} = \underset{-}{\gamma_1} WC + \underset{+}{\gamma_2} (WC)^2 + \underset{+}{\gamma_3} B(1 - D_N)D_S + \underset{-}{\gamma_4} BD_N(1 - D_S) + \gamma_6 BD_N D_S \\ + \gamma_5 B(1 - D_N)(1 - D_S) + \underset{+}{\gamma_7} A^a + \underset{-}{\gamma_8} A^p + \rho AP_{k,t-1} + c_k + u_{k,t} \quad , \quad (4)$$

where c_k represents unobserved heterogeneity. Since we do not observe the premium to ex-ante licensing we must make do with the binary random variable $\Pi_{k,t} = 1$ for $\Pi^*_{k,t} > 0$. Then for a random draw k from the population and $t = 1, 2..T$ let:

$$P(\Pi_{k,t} = 1 | \Pi_{k,t-1}, ..., \Pi_{k,0}, z_k, c_k) = \Phi\left(\boldsymbol{z_{k,t}\gamma} + \rho \Pi_{k,t-1} + c_k\right) \ , \quad (5)$$

denotes the probability that we observe an ex-ante licensing agreement. Here $\boldsymbol{z}_{k,t}$ is the vector of exogenous explanatory variables. This includes the variables set out above. The following subsection sets out how these and other explanatory variables are derived from the data.

3.2 Specification of the empirical model

We model firms' propensities to engage in ex-ante licensing conditional on the decision to cooperate on R&D. Our empirical model is a dynamic binary choice model. The theoretical

[13] This finding is reported by Hernán et al. (2003); Sakakibara (2002); Stuart (1998)

model from which we derive the hypotheses of section 3.1 does not encompass transactions costs effects nor is it dynamic. Dynamic effects may be important however if transactions costs of licensing drop significantly for a given pair after a licensing contract has been signed by that pair in the previous period. In such cases the type of the previous contract may significantly affect the type of the following contract, in effect creating a path dependence for the firm pair. We would like to establish whether such path dependence is likely to arise as this would have policy implications.

In order to allow for state dependence effects we estimate a dynamic binary choice model. Thereby we seek to separate the effects of the variables of interest for our static theoretical model and the component of transactions costs that is specific to a given firm pair and gives rise to dynamic effects.

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 will be unobserved heterogeneity in our data. While methods that allow one to control for unobserved heterogeneity in linear panel models are well understood by now, methods that allow one to deal with the problem in non-linear panel data models have only recently become available. In settings in which dynamic effects are likely to be important, controlling for unobserved heterogeneity is crucial. If the problem of unobserved heterogeneity is ignored it is impossible to exclude that observed state dependence is the "spurious" consequence of serial correlation induced by unobserved heterogeneity.

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

$$P\left(\Pi_{k,t}=1|\,\Pi_{k,t-1},.,\Pi_{k,0},\boldsymbol{z_{k,t}},c_k\right)=\Phi\left(\boldsymbol{z_{k,t}\gamma}+\rho AC_{k,t-1}+c_k\right) \tag{6}$$

where $\Pi_{k,t}=1$, if a firm pair 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.

"Spurious" state dependence arises where there is correlation between the initial condition $\Pi_{k,0}$ and the unobserved heterogeneity. Several solutions to deal with this initial conditions problem are discussed by Hsiao (1986). One of these deals with possible correlation between the initial condition and the unobserved heterogeneity by integrating out the unobserved heterogeneity. To do this it is necessary to specify the distribution of the initial condition, conditional on unobserved heterogeneity. Of course this distribution is not known and any misspecification thereof will yield an erroneous model. Heckman (1981) proposes to pursue this approach by approximating the conditional distribution of the initial condition. Unfortunately this approach is computationally intensive.

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

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 semi-parametric approach that identifies the parameters of the dynamic unobserved effects logit model. 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. Therefore we follow the method suggested by Wooldridge (2005). We estimate a random effects probit 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

$$\Phi(\boldsymbol{z_{k,t}\gamma} + \rho\Pi_{k,t-1} + \delta_0 + \delta_1\Pi_{k,0} + \gamma_k\delta_2 + a_k + u_{k,t}) \; . \tag{7}$$

This is the model we estimate below. We add $\Pi_{k,0}$ and γ_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.

3.3 Definitions of variables

In this section we describe the explanatory variables employed in our model. To test the hypotheses set out above we need to measure the strength of blocking patents (B), the complementarity between one firm's new patents and existing patent stocks of its partner firms(C) as well as the expected value of firms' innovations W. We derive all of these measures from the patent data contained in the NBER patent database. Additionally we employ a measure of the number of firms competing for a new patent N and a measure of the nature of product market interactions between these firms D_S. These measures are derived from the datasets on firms' cooperative agreements and the data on sales and market shares in the semiconductor industry.

To ensure that our results are reliable we have investigated the effect of specific changes in the definitions of these variables. We found that our results are robust to such changes. In the following discussion we focus on our preferred definitions for each variable and indicate which variants we have explored.

All of the variables we employ characterise pairings of cooperating firms. As our dataset contains information on each individual firm we have generally used the average of the individual firms' characteristics to characterise the pair. As we discuss below this form of measure comes closest to the parameters of our theoretical model. Where more than two firms were involved in an R&D contract we have treated each pairing of the firms as a separate observation.

The dependent variable - $\boldsymbol{\Pi}_{k,t}$ 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 ($\Pi_{k,t} = 0$). By investigating the choice between ex-ante and ex-post R&D agreements we condition on the decision to cooperate on R&D.

The strength of blocking patents - $\boldsymbol{B}_{k,t}$ This variable captures the extent to which firms' 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[14] (a), to which all semiconductor patents may be assigned. We assume that firms' patent stocks will be more

[14]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).

likely to be mutually blocking if their average shares of patents over these classes are high. Our measure of B for pair k at time t is defined as follows:

$$B_{k,t} = \sum_{i=1}^{2} \sum_{a=1}^{9} \frac{P_{iat}}{\sum_{i=1}^{n} P_{iat}} * \frac{P_{iat}}{\sum_{a=1}^{9} P_{iat}} \quad , \tag{8}$$

where P_{iat} is the count of the number of patents of firm i in patent class a at time t and n stands for the number of firms active in a patent area. We weight each firm's share of patents in a given patent area by the share of its patenting activity in that area. Then we sum these weighted patent area shares over the patent areas and the firms in the pair.

In an alternative specification we have used an unweighted measure of firms' patent shares in the patent areas to capture blocking. This measure allows us to establish how sensitive our results are to the definition of the patent areas we use. Our main findings are robust, but less precise when we employ this coarser measure of blocking. The unweighted measure gives too much weight to firms' patent shares in patent areas that are relatively unimportant to those firms. Therefore we have preferred the measure set out here.

The forward complementarity - $C_{k,t}$ This variable captures the complementarity between the existing patent stocks held by each firm and the latest 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 forward citations of firms' patents in our measure of forward complementarity C[15]. Our measure of C for the pair k and time t is defined as follows:

$$C_{k,t} = \sum_{i=1}^{2} \sum_{a=1}^{9} \frac{PC_{iaT}}{\sum_{i=1}^{n} PC_{iaT}} * \frac{\sum_{t=0}^{T-1} PC_{iat}}{\sum_{a=1}^{9} \sum_{t=0}^{T-1} PC_{iat}} \quad , \tag{9}$$

where PC_{iat} is the number of forward citations received by the patents of firm i in the patent area a in year t and n stands for the number of firms active in a patent area. We divide this count of citations to firm i's patents by the overall count of forward citations to all firm's patents to yield 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 firms' patent stocks. Once more we sum this measure of the two firms in the firm pair.

In our alternative specification we have used an unweighted measure of this variable in order to establish whether our results are sensitive to the definition of the patent areas we employ. Just as in the case of B there is no evidence that the definition of the patent areas significantly changes our results.

The value of products affected by patents -W This variable measures the expected value to a firm of owning a patent in a given patent area a. It measures the total citations received by the firm's stock of patents in a patent area relative to all citations received by the stock of patents of all firms patenting in that patent area. By using both C and W jointly we seek to

[15]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.

distinguish between the technological value of a patent given by C and the expected stream of returns associated with the patent, which we measure by W. Our measure of W is defined as follows:

$$W_{k,t} = \sum_{i=1}^{2} \sum_{a=1}^{9} \frac{\sum_{t=0}^{T} PC_{iat}}{\sum_{t=0}^{T} \sum_{i=1}^{N} PC_{iat}} \quad , \tag{10}$$

where PC_{iat} is the number of forward citations received by the patents of firm i in the patent area a in year t and n stands for the number of firms active in a patent area.

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 cooperate on R&D ex-ante depend delicately on whether firms are competitors or complementors in the product market.

Unfortunately our data do not allow us to operationalise this variable in a very sophisticated manner. We only observe whether firms have sales in each one of three segments of the semiconductor industry (memory, components, others). We assume that firms are competitors if they both have sales in the same segment of the semiconductor industry at least once.

Transactions costs of ex-ante and ex-post R&D cooperation Our data do not contain any direct measures of the level of transactions costs either for ex-ante or for ex-post R&D agreements. The empirical literature on the choice whether to cooperate on R&D or not typically finds that previous experience of R&D cooperation has a positive effect on the propensity to cooperate again. This finding is commensurate with an interpretation that transactions costs fall as firms gain experience with cooperative r&D agreements.

We employ counts of ex-ante (L^a) and ex-post (L^p) R&D cooperation in a attempt to proxy firms' experience in conducting cooperation agreements of each kind.

The number of firms sharing a new innovation -N This variable measures how large the group of firms is that jointly face the choice between ex-ante and ex-post R&D cooperation. We model this choice and observe this choice as made by firms in our data. We use the observed number of cooperating partners to measure N. This measure is the only one that is consistent with our theoretical model.

Alternative measures would seek to establish which potential partners might have joined the cooperative agreement. Such measures would allow for firms that might have joined a given R&D agreement but did not. As these firms choose not to cooperate on R&D they make a choice which we do not study. Our theoretical model does not deal with coalition formation in cases in which only a subset of firms decides to cooperate. Therefore we have no predictions for such cases. Alternative, wider measures of the number of cooperating firms would be fitting only in a study testing the predictions of such a theory.

Further control variables

- *Aggr. revenues*: Figure 2 suggests that the demand for semiconductors had a strong effect on the propensity of semiconductor firms to cooperate on R&D. It also suggests that this effect was stronger for ex-ante R&D cooperation than for ex-post R&D cooperation. We do not derive predictions about the effects of changes in demand on the propensity to cooperate on R&D and therefore we include this variable in our specification as a control variable.

- *Average market shares*: We include this variable to control for the average size of the firms in an R&D agreement. We do not derive any predictions for the sign of this variable from our theoretical work.

- *Differences in market shares*: Stuart (1998) shows that a cooperative agreement with a firm that is very visible within the industry can bestow prestige on a comparatively smaller firm. He finds that prestige has a strong positive effect on firms' propensity to cooperate on R&D. 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 the prestige which R&D cooperation bestows on the smaller partner in an R&D alliance.

In the next section we set out how we make use of these variables to test the predictions of our theoretical work on the propensity to cooperate on R&D ex-ante.

3.4 Descriptive statistics

We begin by providing descriptive statistics for the firms in our sample, distinguishing between firms that licensed ex-ante and firms that licensed ex-post. Firms that engaged in both types of licensing are represented on both sides of the following table.

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.
Num. of parties	771	2.47	0.98	2	6	1264	2.39	1.16	2	10
Total contracts	771	6.35	11.02	1	44	1264	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
Forw. cits.	504	1056	1341	0	6282	657	1145	1413	0	6282

Table 2 shows that there are 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 discussed in section 2. The average firm in our sample engages in licensing contracts with one or two further parties. In total the average firm engaged in approximately 6 such contracts between 1989 and 1999. The average firm was granted 128 /137 patents and its patent stock attracted a total of 1056/1145 citations over the sample period. All of these variables are highly skewed.

Table 3 below provides descriptive statistics for pairs of licensing firms that we observe in our data. Each licensing contract between N firms gives rise to $N(N-1)$ firm pair observations. The table has two sections. The first provides descriptive statistics on individual variables that do not directly enter our regressions. The second provides descriptive statistics for the explanatory variables which we include in our regressions. Some of the latter are constructed by interacting variables from the first part of the table.

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

	Ex-post licensing ($N = 258$)				Ex-ante licensing ($N = 321$)			
Variable	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
D_N $(N > 2)$	0.53	(N=138)			0.46	(N=150)		
$(1 - D_S)$ (Complements)	0.38	(N=99)			0.39	(N=125)		
B	0.123	0.087	0	0.416	0.106	0.085	0	0.354
C	0.325	0.872	0	3.182	0.241	0.741	0	3.273
W	0.032	0.022	0	0.113	0.028	0.022	0	0.093
CW	0.005	0.006	0	0.028	0.004	0.005	0	0.029
$B(1 - D_N)D_S$	0.008	0.023	0	0.113	0.194	0.731	0	3.273
$BD_N(1 - D_S)$	0.102	0.551	0	0.145	0.005	0.023	0	0.328
$B(1 - D_N)(1 - D_S)$	0.036	0.28	0	3.18	0.018	0.18	0	3.2
$BD_N D_S$	0.18	0.664	0	3.178	0.024	0.047	0	0.358
Av. mkt. shares	3.2%	2.4%	0	8.3%	3.1%	1.9%	0	9.9%
Diff. mkt. shares	0.029	0.029	0	0.163	0.033	0.03	0	0.16
Aggr. Revenues 10^9\$	85.6	37.2	52.8	169.3	94.7	37	52.8	152.9
L^p	8.33	8.16	1	38	6.69	6.54	0	38
L^a	8.13	6.66	0	28	9.41	6.87	1	36
$\Pi_{k,0}$	0.09	(N=22)			0.04	(N=12)		

In the upper part 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 $B(1-D_N)D_S$ (Hypothesis 2) and $BD_N(1-D_S)$ (Hypothesis 3) 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 strongly associated with a high blocking strength of existing patent portfolios when just two product market competitors contract with one another. Similarly ex-post licensing is more strongly associated with a high blocking strength of existing patent portfolios when more than two producers of complementary products contract. This is the prediction of Hypothesis 3. In the following section we test whether these patterns are statistically significant in a multivariate analysis.

4 Results

We refer to the dynamic random effects probit discussed in section 3.2 above as specification (3) below. Together with this specification we also estimate a binary choice probit model (1) and a binary choice probit which includes a lagged dependent variable (2). The comparison between the results of specifications (1) and (3) will show whether there is any significant effect of unobserved heterogeneity in our data. We also provide specification (2) to establish whether there is evidence of state dependence in the data. If there is also evidence for unobserved heterogeneity, then the results of estimating specification (2) will be inconsistent.

The results from estimation of these three specifications are set out in Table 4 on the following page. We report both the parameter estimates and the corresponding elasticities. The elasticities in specification 3 are averages over the distribution of the unobserved heterogeneity at the sample mean. The first six parameters set out in the table capture our hypotheses 1-3. The effects of previous experience with licensing are captured by the variables L^a, L^p and the lagged dependent variable.

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

Explanatory variables	(1)	Elast.	(2)	Elast.	(3)	Av. Elast.
CW	-112.48 ***	-0.04	-127.96 ***		-136.85 ***	-0.22
	(29.54)	(0.03)	(30.61)		(40.42)	(0.14)
$(CW)^2$	2024.25		2502.80 *		2760.96	
	(1378.12)		(1408.36)		(1705.81)	
$B(1-D_N)D_S$	17.32 ***	0.22	14.90 ***		17.74 ***	1.25
	(2.85)	(0.09)	(3.07)		(3.63)	(0.20)
$BD_N(1-D_S)$	-4.39	-0.02	-3.036		-7.26 *	-0.22
	(3.34)	(0.03)	(3.55)		(3.99)	(0.15)
$B(1-D_N)(1-D_S)$	-0.01	0.00	-0.04		0.24	-0.004
	(0.24)	(0.001)	(0.24)		(0.25)	(0.004)
BD_ND_S	-0.78 *	-0.01	-0.86 *		-1.10	-0.07
	(0.43)	(0.01)	(0.46)		(0.68)	(0.05)
$\Pi_{k,t-1}$	-	-	0.52 **		0.71 **	0.44
	-	-	(0.26)		(0.35)	(0.25)
$\Pi_{k,0}$	-	-	-		-0.88 ***	-0.03
	-	-	-		(0.31)	(0.01)
Av. mkt. shares	-12.70 ***	-0.05	-16.11 ***		-22.15 ***	-0.44
	(3.98)	(0.03)	(4.34)		(5.67)	(0.16)
Diff. mkt. shares	7.43 ***	0.03	8.04 ***		10.45 ***	0.20
	(2.57)	(0.02)	(2.59)		(3.41)	(0.08)
Aggr. Revenues 10^{-7}	-2.60	-0.03	-0.00**		-70.10 **	-0.40
	(18.90)	(0.02)	(0.00)		(31.40)	(0.20)
D_N	0.78 ***	0.04	0.64***		0.78 ***	0.25
	(0.16)	(0.02)	(0.18)		(0.22)	(0.07)
$(1-D_S)$	0.17	0.01	-0.04		0.29	0.07
	(0.15)	(0.01)	(0.18)		(0.24)	(0.06)
L^p	-0.07 ***	-0.06	-0.07 ***		-0.09 ***	-0.42
	(0.01)	(0.03)	(0.01)		(0.02)	0.14
L^a	0.09 ***	0.10	0.11 ***		0.12 ***	0.69
	(0.02)	(0.05)	(0.02)		(0.02)	(0.21)
Log-Likelihood	-322.17		-320.1		-294.45	

where ***, **, * indicate significance at the $0,01\%$, $0,05\%$ and the $0,1\%$ levels.

Table 4 shows that the signs and significance of all the variables of interest are stable across the three specifications. The results generally support our hypotheses and also suggest that transactions costs have a significant impact on firms' choices between ex-ante and ex-post licensing.

Of the three specifications we estimate, we prefer the third because it allows for state dependence and deals with the initial conditions problem in the manner suggested by Wooldridge (2005). In this specification the initial condition itself ($\Pi_{k,0}$) is significant which indicates that there is unobserved heterogeneity in our data. The remaining parameters are also strongly affected by the attempt to control for this heterogeneity. Therefore we focus our discussion of the results on specification 3.

Predictions on the expected value of licensing The hypotheses set forth in section 3.1 above are all supported in our specifications. As hypothesised there is indeed a U-shaped relationship between the probability of observing ex-ante licensing and an increase in the value of the patent. This hypothesis is captured by the parameters WC and $(WC)^2$ which are jointly significant. The minimum point of this quadratic function is at $WC = 0.025$ and the quadratic crosses the x-axis at $WC = 0.05$ which is far beyond the sample mean of WC at 0.0047. Thus for the larger part of the sample an increase in the value of an innovation will have the effect of reducing the probability of observing 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 1% increase of the expected value will lead to a reduction in the probability of observing ex-ante licensing by 0.22%. The sign of the effect is robust to our controls for unobserved heterogeneity and state dependence. The effect is one order of magnitude greater in our prefered specification than in the probit in specification (1).

The hypotheses regarding the effects of greater blocking strength of existing patent stocks are also borne out in the data. Hypothesis 2 is captured by the parameter on ($B(1 - D_N)D_S$) which is significant at the 1% level in all three specifications. Our results indicate that an 1% increase in the expectation of the blocking strength of a rival firms' patents increases the probability that ex-ante licensing is observed if firms are product market competitors by 1.25%. The descriptive statistics in Table 3 above show that the measure of the blocking strength of rivals' patents can be three times as large as the mean level. 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 to each other ex-ante. It should be noted that the elasticity of ex-ante licensing with respect to the blocking strength of rivals' patent portfolios is an order of magnitude weaker in specification (1).

Hypothesis 3 is captured by the parameter on ($BD_N(1 - D_S)$) which is just significant at the ten percent level in specification 3. This parameter is only significant when we control for unobserved heterogeneity and the effects of a lagged dependent variable. However the coefficient has the hypothesised sign throughout. The implication of this finding is that greater blocking strength of patents increases the probability of observing ex-post licensing if more than two complementors contract with one another. The elasticity of ex-ante licensing with respect to this parameter implies that a 1% increase in the blocking strength of complementors' patent stocks will decrease the probability of observing ex-ante licensing by 0.22%. This effect is much weaker than that of ex-ante licensing on the choice of the type of licensing contract by competing firms. This elasticity is also an order of magnitude greater than that in specification (1).

The remaining interaction terms ($B(1 - D_N)(1 - D_S), BD_N D_S$) capture cases in which theory suggests that the direct and indirect effects of licensing ex-post work in opposite directions. Therefore we were unable to provide any predictions on the signs of these variables. Our results do not allow us to conclude which effect is stronger as neither variable is significant in specification 3.

Overall we interpret these findings as strong evidence in favour of the validity of the theoretical model set forth in *vGS* which we discuss in section 3.1 above.

Transactions costs Here we distinguish between the general effect of previous experience with licensing and firm pair specific effects. The latter are captured by the lagged dependent variable that indicates whether a pair was engaged in ex-ante licensing in the previous period. The test for state dependence is given by $H_0 : \rho_1 = 0$. As our results show we can reject the null hypothesis that the lagged dependent variable is not significantly different from zero at the 1% level. The impact of state dependence is strong in comparison with the effects of the blocking strength of existing patents. If we compare two pairs of firms that differ only in their experience of ex-ante licensing in the previous period, then that pair which has previous experience with ex-ante licensing, has a probability of choosing an ex-ante contract again that is 0.44% higher, than that of the firm pair which has no experience of licensing in that period.

In order to avoid a common problem with categorical response models, the separation problem, we include only first-order lagged endogenous and exogenous variables. In the context of licensing data the first-order restriction is unlikely to cause a major problem as first lags may not be statistically significant even though higher-order lags are statistically significant.[16]

The variables counting the number of previous licensing contracts entered into by the firm pair are both significant at the 1% level in every one of our specifications. We interpret this as evidence that transactions costs fall if firms have previous experience of licensing. Previous experience of ex-ante and ex-post licensing in any period have differing impacts on the probability of licensing ex-ante in the current period. In particular an increase of previous experience of licensing by ex-ante licensing contract increases the probability of licensing ex-ante in the current period by 8.6% at the sample mean. In contrast an additional ex-post licensing contract will reduce the probability of licensing ex-ante in the current period by 5.3% at the sample mean.

Other control variables In section 2 we noted that there was a dramatic reduction in the number of ex-ante licensing contracts after 1996 which coincided with a fall in the growth rate of aggregate revenues in the semiconductor industry. Therefore we included aggregate revenues as a control variable in our specifications. We find that this variable is significant at the 5% level once we allow for state dependence. Specification (3) suggests that the increase in aggregate revenues should have had a negative effect on firms' propensity to license ex-ante. We have no hypothesis to offer that would explain this effect. It runs counter to the interpretation which was suggested in section 2 on the basis of our data description.

It should be noted that the associated elasticity is almost as strong as that of state dependence with the opposite sign. As aggregate revenues are decreasing for 2 of the 11 years of our sample it is possible that the variable is picking up the effects of state dependence in specification (1). This would explain why it is not significant there.

Our results also show that there is no significant effect of the form of product market competition (D_S) that goes beyond that captured by the interacted variables discussed above.

[16] The separation problem is caused by some model parameters being theoretically infinite. This can happen when the model nearly perfectly, predicts the response (i.e., separates the response levels). It is a common result of the data being sparse, meaning that not all response levels are observed in each of the predictor settings. One possible solution to the separation problem is to reduce the number of variables.

However we find that ceteris paribus firms which enter into licensing contracts with more than two partners (D_N) are far more likely to sign ex-ante licensing contracts than firms that enter into licensing contracts with just one other party. This effect is significant at the 1% level in all of our specifications. Our results suggest that the probability of observing ex-ante licensing is 25% higher in contracts with several parties than in bilateral contracts.

Overall these results show that the choice between ex-ante and ex-post licensing depends both on the strategic circumstances a firm finds itself in and its past experience of particular forms of licensing. Both greater blocking by product market rivals and previous experience of ex-ante licensing are found to have very strong positive effects on the probability that firms will choose to license ex-ante.

Furthermore we find that while ex-ante licensing is more likely to arise between product market rivals, ex-post licensing is more likely to arise between firms whose products complement each other. We argue in *vGS* that firms are choosing the form of licensing that the social planner would also prefer in each of these circumstances.

5 Conclusion

In this paper we investigate the choice between ex-ante and ex-post licensing in an industry affected by the patent thicket. To do this we construct a dataset of licensing contracts in the semiconductor industry. We explore the main trends in licensing in this industry. We find that ex-ante licensing was surprisingly popular amongst firms in this industry until 1996, when its popularity declined very rapidly. Our data also show that licensing contracts are predominantly bilateral and that there is a large proportion of firms that engages in both ex-ante and ex-post licensing. Amongst these we find firms such as Intel and Texas Instruments that are usually cited in studies of ex-post contracts.

To explain the variation in firms' choices between ex-ante and ex-post licensing contracts we develop an empirical model. This encompasses the strategic effects of hold-up within the patent thicket and reductions in transactions costs arising from previous experience with licensing contracts of either kind. This empirical model is partly derived from theoretical work in *vGS* which we summarise in section 3.1.

We estimate a dynamic random effects probit model to test the predictions of our empirical model. 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. To distinguish between spurious state dependence caused by unobserved heterogeneity and real state dependence we control for unobserved heterogeneity in the way suggested by Wooldridge (2005). We find strong evidence of unobserved heterogeneity as well as evidence for the existence of state dependence in our data. We also find evidence to suggest that past experience of contracting in a particular way makes it more likely that firms will choose that form of contracting again.

These findings suggests that particular firm pairs and individual firms may get locked into a particular form of licensing. This makes the formulation of public policy towards licensing doubly hard as little is known about the effects of regulation in the presence of path dependence.

The results of our empirical work also confirm the importance of blocking of new patents by existing patent portfolios in explaining the licensing behaviour of firms within the patent thicket. We find that a theoretical model of a patent race for a patent which is a complement to existing patents provides predictions which are borne out in our data. We show that stronger blocking patents lead to more ex-ante licensing between product market rivals and more ex-post licensing between firms that produce complementary products. Given the paucity of previous empirical evidence supporting the relevance of patent race models to industries in which firms patent it is interesting to find that they may be applied profitably to strategic patenting within the patent thicket.

Our theoretical work on the impact of licensing on firms' R&D investment incentives is supported by our empirical results in this paper. Building on this theoretical model we derive welfare results which suggest that firms will tend to choose the socially preferable form of licensing if they are free to do so. This also reinforces the note of caution sounded above regarding the regulation of licensing in the semiconductor industry. Such regulation should take care not to influence the choice between ex-ante and ex-post licensing that firms would privately make.

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A A simple model

Here we set out a simplified version of the model we develop in von Graevenitz and Siebert (2005) to derive the Hypotheses 1 - 3. We make an assumption about the functional form of the R&D cost function which leads to an analytical solution of the second stage of our model. In *vGS* we avoid making such an assumption and show that the results we obtain here also apply more generally.

The three stages of our model are discussed in section 3.1 above. At the third stage of the model firms bargain over the surplus created by new patents. Bargaining can only arise 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 asume 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:

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

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

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:

$$V^a = \frac{(h^a + H^a)\frac{\bar{\pi}}{r} + \pi - K(h^a + r)}{h^a + H^a + r} \tag{13}$$

$$V^p = \frac{\frac{v_W}{r}h^p + \frac{v_L}{r}H^p + \pi - K(h^p + r)}{h^p + H^p + r} \tag{14}$$

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[17].

[17]If we undertake comparative statics on the value of v_W, as we do below it must be true that $\frac{\bar{\pi}}{r} > K > \frac{(\bar{v_W} - v_L)}{r}$, 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.

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:

$$\frac{[(\bar{\pi}-\pi)-KH^a]}{(h^a+H^a+r)^2}=0 \Leftrightarrow \hat{h}^a=\frac{(\bar{\pi}-\pi)}{K(N-1)} \tag{15}$$

$$\frac{\left[\frac{(v_W-v_L)}{r}H^p+(v_W-\pi)-KH^p\right]}{(h^p+H^p+r)^2}=0 \Leftrightarrow \hat{h}^p=\frac{r(v_W-\pi)}{(Kr-(v_W-v_L))(N-1)} \tag{16}$$

These characterise interior optima[18] and we solve for the value functions at these optima next:

$$V^a(\hat{h}^a)=\frac{N\hat{h}^a\frac{\bar{\pi}}{r}+\pi-K(\hat{h}^a+r)}{N\hat{h}^a+r}=\frac{\bar{\pi}}{r}-K \tag{17}$$

$$V^p(\hat{h}^p)=\frac{\frac{(v_W-v_L)}{r}\hat{h}^p+\frac{v_L}{r}(N\hat{h}^p+r)-(v_L-\pi)-K(\hat{h}^p+r)}{N\hat{h}^p+r}=\frac{v_W}{r}-K \tag{18}$$

The premium to ex-ante licensing is defined as $\Pi=(V^a-V^p)+(T^a-T^p)$ above (Ein. (1)). The model developed here allows us to derive hypotheses about (V^a-V^p). As long as the transactions 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 the expected values of licensing ex-ante and ex-post:

$$V^a-V^p=\frac{1}{r}(\bar{\pi}-v_W)=\frac{(N-1)}{2r}\left[\pi_L(b,C)+\pi_W(b,C)-\frac{2}{(N-1)}\pi_W(B,C)\right]-\frac{(N-2)}{r}\bar{\pi}(C) \tag{19}$$

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).

Hypothesis 1 Due to the fact that the R&D cost function in our example is linear in firms' R&D investments we can only demonstrate that a stronger forward complementarity between the new patent and existing patents will reduce the probability of observing ex-ante licensing. In the more general setting of *vGS* we find that the relationship between the forward complementarity and the probability of observing ex-ante licensing is U-shaped.

Equation (19) 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.

[18] 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.

$N > 2$: 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 (19) simplifies to:

$$(V^a - V^p) = \frac{1}{2r}\Big[\pi_L(b,C) - \pi_W(b,C)\Big] \tag{20}$$

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; it is more likely that ex-ante licensing may be observed. This is an example for Hypothesis 2.

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 ($\frac{\partial \pi_L}{\partial b} < 0$). As is obvious from equation (19) a reduction of the positive terms in this expression increases the probability that ex-post licensing has a greater expected value than ex-ante licensing. This is an example of Hypothesis 3.

B Examples for Ex-ante and Ex-post Licensing

In the following, we present some examples for ex ante and ex post licensing contracts, taken from our database.

EX-ANTE LICENSING

Memory

- 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: 19951120.

- Paradigm Technology Inc and NKK Corp formed a joint venture to develop next generation SRAM semiconductor process architecture. Specific and financial terms of the agreement were not disclosed. Date: 19960426.

- Advanced Micro Devices Inc and Fujitsu Ltd entered into a joint agreement to to develop a 3.3-volt 8-megabit flash memory in Japan. The equally owned company was called Fujitsuamd Semiconductor Ltd. The product was called MBM29LV800. The first product the venture developed was a 5.5 volt flash memory. Financial terms of the agreement were not disclosed. Date: 19960301.

- Samsung of South Korea and Siemen's AG formed a licensing agreement to produce and market chip-card memory chip. Specific financial terms were not disclosed. Date: 19951120.

Microcomponents

- Apple Computer Inc, International Business Machines {IBM} and Motorola Inc formed a strategic alliance to research and develop, manufacture and wholesale PowerPC 750 microprocessors in the United States. Financial terms were not disclosed. Date: 19980317.

- Sony Corp and Fujitsu Ltd planned to form a strategic alliance to provide research, development and manufacturing of large-scale integrated circuit chips in Japan. The SA was to use the production system of LSI chips using 0.18-micron process technology. The most important application for the new chips will be for products that are more sensitive to power consumption, portability and compactibility. Financial terms were not disclosed. Date: 19980106.

- Hitachi Ltd (HL) and SGS-Thomson Microelectronics (ST), a unit of STMicroelectronics NV, formed a strategic alliance to provide research and development services of super microprocessors for consumer electronics and multi media applications in Japan and France. The 64-bit sh-5/st50 series was to be based upon HL's sh-5 superh architecture and ST's st50 64-bit microprocessors. The alliance was to also allow ST to have access through specific licenses to HL's sh-3 and sh-4 series. Date: 19971209.

EX POST LICENSING

Memory

- 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: 5/8/1995.

- Intel Corp granted Catalyst Semiconductor Inc a license to its flash memory technology. Catalyst Semiconductor designs and markets nonvolatile semiconductor memory products. Specific and financial details were not disclosed. Date: 950901.

- Logic Devices, Inc. and Oki Electric Industries Co., Ltd. signed a memorandum of understanding, in which Logic Devices was to grant Oki Electric a license to use its 1 megabit static random access memory(SRAM) chip technology. In return, Oki Electric was to provide foundry and production for Logic Devices. The agreement was announced with Logic Device's disclosure that it and AT&T Microelectronics had decided to terminate their agreement over the next year. Date: 920615.

Microcomponents

- National Semiconductor Corp. has licensed its printer/display processor (SN32CG13) to Samsung Electronics Co. Ltd. Samsung will use the processor to produce a product that will be a low-cost alternative to Adobe Systems' Postscript and Hewlett-Packard's laser printers. The product will be fully compatible with both. Date: 890905.

- Zilog has signed an agreement with Hewlett-Packard's Circuit Technology group granting HP a nonexclusive license to the Z80 8-bit microprocessor as an application-specific IC core. HP will enter the Z80 into its ASIC library for use in internal ASIC designs. HP has also used the Z80 in its laser jet printers. Financial terms of the agreement were not disclosed. Date: 910819.

- 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: 941005.

C Data description

Table 5: Revenues and numbers of firms in the sectors of the semiconductor industry.

	Semiconductor Sector		Memory Sector		Microcomps. Sector	
Years	Revenues*	No. of firms	Revenues*	No. of firms	Revenues*	No. of firms
1989	52,751	131	14,502	48	7,789	51
1990	54,578	139	12,107	51	9,575	54
1991	59,341	131	12,668	51	11,763	59
1992	64,774	156	15,425	58	14,315	72
1993	85,328	152	23,274	56	19,970	77
1994	109,402	153	33,394	54	26,393	79
1995	152,875	171	55,842	55	35,293	84
1996	143,402	157	38,480	52	42,331	84
1997	150,911	171	31,324	55	51,360	87
1998	138,747	187	24,438	54	49,316	92
1999	169,311	166	34,591	48	57,018	88
Average	107,099	156	26,913	53	29,557	75

*=measured in Mio $-US of 1989

Table 5 above displays statistics on industry revenues and number of firms in the semiconductor industry as a whole, as well as the memory and the microcomponents segments, of all firms producing for at least one year in the semiconductor industry worldwide from 1989 to 1999. In the 1990's, competition in the semiconductor industry increased dramatically, brought on by the larger number of firms, which rose from 132 in 1989 to 188 in 1998. The semiconductor industry generated annually $107,402$ Mio. US-$ on average from 1989 to 1999. The memory and the microcomponents markets make up for 50% of the sales in the semiconductor industry, with each generating between 25 and 30 billion US-$, on average. The microcomponents segment grew much faster than the memory segment over the period of investigation. On average, 54 firms operated in the memory and 75 firms in the microcomponents segment in a given year during the $1989-1999$ period. Again time trends are interesting: while the number of firms stayed nearly constant in the memory segment, the microcomponents segment is characterized by positive net entry over the $1989-1999$ period (the number of firms increased from 51 in 1989 to 88 in 1999).

Table 6 shows statistics on the number of ex ante and ex post licensing deals. There are 549 ex-ante and 372 ex-post licensing contracts that have been signed during the $1989-1999$ period. In the memory industry 93 and 62 ex- ante and ex-post licensing contracts have been formed. In the microcomponents industry we find 127 and 47 contracts, respectively. The table also shows how the number of ex-ante and ex-post contracts changed over the sample period. It is noticeable that there was a tremendous increase in the number of ex-ante contracts at the beginning of the sample period. There is an equally dramatic reduction in numbers after 1994.

	Semiconductor		Memory		Microcomponents	
Years	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**
1989	22	21	6	7	5	5
1990	38	36	6	8	9	4
1991	84	27	10	3	17	5
1992	78	38	17	15	27	8
1993	89	31	15	2	24	4
1994	103	32	14	2	23	5
1995	58	27	12	6	9	2
1996	23	12	5	1	2	3
1997	40	27	4	5	9	1
1998	12	25	2	4	2	4
1999	8	22	2	2	0	2
sum	555	298	93	55	127	43
avg	50	27	8.5	5	11.5	3.9

Table 6: Number of Ex-ante and Ex-post R&D cooperation agreements in the semiconductor industry 1989-1999

D Further results

Here we report further empirical results. Before estimating our model as discussed above we undertook exploratory work with simpler definitions of our variables B and C. In the results reported here we used unweighted versions of these variables. As the table shows our results in this case are broadly in line with those reported above. That means that all the sign restrictions which our theoretical model predicts are borne out.

The main differences between the two sets of results are that the parameters capturing Proposition 2 are significant here, whereas those capturing Proposition 3 are not. In table 4 above the parameters capturing Proposition 3 are significant but those capturing Proposition 2 are not. We preferred the definitions of B and C that use weights as we believe that these are better measures of blocking than the rather coarse measures we use below.

Nonetheless it is comforting to know that our results are fairly robust to variations in the way in which the strength of blocking patents and the forward complementarity are measured.

Table 7: Results - Dependent variable $\Pi_{k,t}$

Explanatory variables	(1)	Marginal effects	(2)	Marginal effects	(3)	APE
$B(1-D_N)D_S$	2.54***	.	2.08***		2.99***	.
	(0.50)	.	(0.55)		(0.65)	.
$BD_N(1-D_S)$	-2.66***	.	-2.63***		-3.29***	.
	(0.78)	.	(0.77)		(1.09)	.
$B(1-D_N)(1-D_S)$	-1.54**	.	-1.72***		-1.43*	.
	(0.64)	.	(0.65)		(0.82)	.
BD_ND_S	-0.81	.	-1.05**		-1.31*	.
	(0.50)	.	(0.51)		(0.67)	.
WC	-7.99	.	-8.48		-13.46*	.
	(6.22)	.	(6.20)		(7.60)	.
$(WC)^2$	4.21	.	8.06		50.03	.
	(43.51)	.	(43.63)		(47.17)	.
$\Pi_{k,t-1}$	-	.	0.45*		1.90***	.
	-	.	(0.25)		(0.63)	.
$\Pi_{k,0}$	-	-	-		-1.52	.
	-	-	-		(1.10)	.
Av. mkt. shares	-10.64***	.	-13.35***		-10.57*	.
	(4.04)	.	(4.35)		(5.62)	.
Diff. mkt. shares	5.89**	.	6.21**		4.59	.
	(2.57)	.	(2.58)		(3.29)	.
D_N	-0.00*	.	-0.00**		-0.00***	.
	(0.00)	.	(0.00)		$(6.11E-6)$	.
$(1-D_S)$	0.63***	.	0.54***		0.46*	.
	(0.18)	.	(0.19)		(0.25)	.
L^p	0.37**	.	0.21		0.74***	.
	(0.17)	.	(0.20)		(0.25)	.
L^a	-0.07***	.	-0.07***		-0.092***	.
	(0.01)	.	(0.01)		(0.02)	.
$\hat{\sigma}_a$	0.11***	.	0.12***		0.14***	.
	(0.02)	.	(0.02)		(0.03)	.
Log-Likelihood value	-331.93		-330.36		-302.05	

where ***, **, * indicate significance at the $0,01\%$, $0,05\%$ and the $0,1\%$ levels.