Market Effects of Patent Reform in the U.S. Semiconductor Industry

Jeff Thurk*
University of Notre Dame

December 2012

Abstract

I study the US Semiconductor industry in the context of 1980s legal reform which strengthened intellectual property rights. Prior to the reform, the industry was highly concentrated in a few vertically-integrated firms. Post reform, the entry of small design firms led to a fragmented industry composed of both specialty design firms and traditional production firms. I ask how much of this change in market structure can be attributed to patent reform and how much was the result of positive demand shocks related to increased IT spending in the economy. I introduce a structural model of innovation and patenting in which the entry rate of specialized design firms can increase due to either an increase in patent protection or demand. I fit the model to industry steady-state and transitional dynamics using data on firm financial performance and patenting behavior. Policy experiments indicate the effects of increased patent protection are minor compared to increased demand.

*I thank Dean Corbae, Ken Hendricks, and Eugenio Miravete for comments and suggestions. The usual disclaimer applies. Correspondence: Department of Economics, University of Notre Dame, 711 Flanner Hall, Notre Dame, IN 46556. Email: jthurk@nd.edu

1 Introduction

The semiconductor industry is quantitatively important to the global economy as it enables nearly every facet of modern life. The industry is highly-competitive and fast-paced as firms dedicate substantial resources creating and protecting new products. It has also changed substantially. During the 1970s and early 1980s, the industry was dominated by integrated device manufacturers (IDMs) which design, manufacture, and sell integrated circuits. This changed during the mid 1980s as the "fabless" business model gained popularity. Fabless manufacturers design and sell their products but outsource the production to third-party, low-cost foundries. Today, fabless firms account for roughly half of the firms in the semiconductor industry.

Why did this shift occur? Hall and Ziedonis (2001) argue that the increase in US patent law during the mid 1980s increased the attractiveness of the fabless business model. In particular, they show the increase in patent law is positively correlated with firm patenting effort and this is particularly true of fabless firms. Their evidence suggests that stronger patent rights enable these firms to enter the industry by securing venture capital funds and protecting niche markets.

Another potential cause is increased demand as greater potential profits increase the attractiveness of market entry. The industry observed substantial growth during the period in question. Real market size (defined as price deflated total revenue) was \$86 billion in 2000, compared to \$12 billion in the early 1980. This substantial growth was largely driven by increased spending on information technology infrastructure and personal computers.

The goal of this paper is to understand the interaction of these effects and to quantify the extent to which stronger patent laws alone generated the observed change in market structure in the US semiconductor industry. I answer this question through the lens of a model. The advantage of this approach is twofold. First, the model provides a tool to show how changes in patent law and demand both effect the composition of IDM and fabless firms. Second, the model provides a lens to isolate the effects of changes in patent law and demand in a controlled environment.

The model is a modification of the standard Ericson and Pakes (1995) model to include licensing and patenting decisions. Firms choose to enter, conduct R&D, spend resources on increasing their patent stock, and exit the industry. Firms gain value through both traditional production and licensing revenue, where the latter is a function of their stock of patents. In equilibrium, stronger IPR protection and positive demand shocks can both lead to increased entry of fabless firms as they use licensing revenue to overcome fixed costs of entry.

I fit the model to industry steady-state and transitional dynamics using data on firm financial performance and patenting behavior. I then conduct two experiments to isolate the effects of changes in patent protection and demand. The results indicate that while increasing patent protection does have an effect on market structure, the effect is small relative to the increase in demand. This is consistent with a large literature which argues that the observed increase in patenting did not reflect a substantial increase in innovation.

The following section discusses US patent reform and the US semiconductor industry in more detail. Sections 4 introduces the model and equilibrium concept. Section 5 provides details on the estimation and presents the results. In Section 6, I use the model to investigate the relative effects of increasing IPR protection and demand on market structure. I provide concluding remarks in Section 7.

2 Related Literature and Contribution

This paper represents a contribution to the a large empirical literature which asks whether increased protection leads to increased innovative effort. Kortum and Lerner (1998) use aggregate cross-country patenting data to ask whether changes in US patent law led to the observed increase in patent propensity in the US. They find that the increase in patenting is due to an increase in firms' ability to manage their R&D resources and not to changes in US patent law. Boldrin and Levin (2008) provide a survey of studies across a range of industries, noting that many industry studies find little to no evidence linking increased patent protection with increased innovation.

In the semiconductor industry, early studies focused on the patenting motives,[1] while later studies have focused on linking patenting behavior with R&D expense. Hall and Ziedonis (2001) is the most relevant paper to this one. The authors reason that the aggregate data used in Kortum and Lerner (1998) hid industry-specific effects of the shift in patent protection. Using both empirical and survey evidence, they conclude that patent reform had two effects. First, it promoted fragmentation by enabling fabless firms to enter and secure their place in the industry. Second, it resulted in large firms becoming engaged in patent portfolio races in order to streamline future innovation.

Their results are supported by Hunt (1996), who finds evidence of a significant shift in competition during

[1] See Tilton (1971), Taylor and Silbertson (1973), Levin (1982), and von Hippel (1988).

the late 1980s or early 1990s. Whereas reverse-engineering had previously enabled innovations to diffuse to competitors, his empirical results indicate that semiconductor firms moved to protect their innovations with patents. The consequence was a shift towards creating next-generation technologies based on competitors' licensed, rather than imitated, ideas.

Both Hall and Ziedonis (2001) and Hunt (1996) offer compelling evidence that the change in US patent law did affect firm patenting decisions. My findings, however, indicate that the change in US patent law did indeed increase patenting intensity but had relatively little real effect on "real" variables such as industry composition and innovation. Hence, my results are more consistent with Kortum and Lerner (1998).

It is important to note that this paper differs from the above literature methodologically as I develop a dynamic model of endogenous innovation and patenting. The advantage of this approach is that the model provides a controlled environment to disentangle the effects of stronger patent laws from increased demand.

3 Background

3.1 US Patent Reform

In 1982 Congress created the Court of Appeals for the Federal Circuit (CAFC) in hopes of unifying case law regarding patent claims. While unifying patent judgments does not necessarily imply stronger protection, the court's subsequent pro-patent judgments increased the value of patent rights. Prior to the creation of CAFC, district appeals courts invalidated patent claims approximately 60 percent of the time. In the following years, this number fell to approximately 30 percent.[2]

There were also several high profile judgments which demonstrated the change in US patent law. The first was Polaroid's 1986 successful patent infringement lawsuit against Kodak which resulted in Kodak paying roughly $1 billion in damages and its subsequent removal from the instant-film camera business. The second was a series of patent lawsuits in 1985 and 1986 by Texas Instruments to defend a set of patents related to their integrated circuit technology.

These lawsuits provide insight into two important points. First, the success of these lawsuits indicates the determination of US courts to protect patents. For this paper, the cases show that the change in US patent

[2] See Hunt (1999)

law resulted in stronger patent rights and these stronger rights had the potential to have real effects on industry structure, competition, and innovation. Second, these lawsuits are simply examples of evolving case law stemming from the 1982 formulation of the CAFC. As such US patent law became stronger over a period of years. This generates an identification issue for any econometrician hoping to understand the effects of the change on industry behavior.

3.2 The US Semiconductor Industry

Semiconductor firms are those firms engaged in the design and/or fabrication of semiconductors, where a semiconductor is any material whose electrical conductivity has values between that of a conductor and a insulator (e.g., light-emitting diodes (LED), transistors, and integrated circuits). While the industry provides products for a wide-variety of hi-tech industries, personal computers still account for the majority of industry sales. Comparative advantage comes through innovation and innovation is a fast-paced, cumulative effort in which tomorrow's new product depends heavily on a broad set of today's products and ideas.

Listed below are the key features of the industry:

A. Competition is Global

Semiconductor firms tend to be large and international in scope, with most of the major players located in Japan, Korea, and the United States. In this paper, I focus attention on domestic US firms and sales.

B. Semiconductors Drive Economic Growth

The semiconductor market forms the backbone of the hi-tech industry, hence is a prime driver of economic growth. For example, the industry's $204 billion in 2004 global sales, enabled $1.2 trillion in electronic systems business and $5 trillion in business services, or approximately 10% of global GDP.[3]

While the above points indicate that this is an important industry, the following points discuss how the industry works.

[3] http://en.wikipedia.org/wiki/Semiconductor_industry

C. The Industry Moves Fast

The industry moves and evolves at an incredibly fast pace, perhaps best exemplified by what has become known as Moore's Law. In a 1965 paper, Intel co-founder Gordon E. Moore noted that the capabilities[4] of the integrated circuit doubled roughly every 18 months - a prediction that has held remarkably true in the 40 plus years since.

Moore's Law also speaks to the short-life associated with any current product and the need to develop tomorrow's great idea today. Accordingly, R&D comprises a significant component of firm expense and this dependence is on the rise.

Table 1: Median R&D Expense

Period	% of Rev.
1975-1989	0.09
1990-1995	0.11
1996-2000	0.14
2000-2007	0.19

D. Firms Protect their Intellectual Property

Several papers have noted a large increase in US patenting since the mid 1980s. Figure 1 illustrates this increase. First, note that the increase in patenting does not increase immediately after the creation of the CAFC, but rather during and after the series of pro-patent rulings in the latter half of the 1980s.

[4] At the time, he was referring to the number of transistors a firm could inexpensively place on a single silicon wafer. Today, advancement generally refers more generically to processor speed.

Figure 1: **Patent Applications Across Industries**

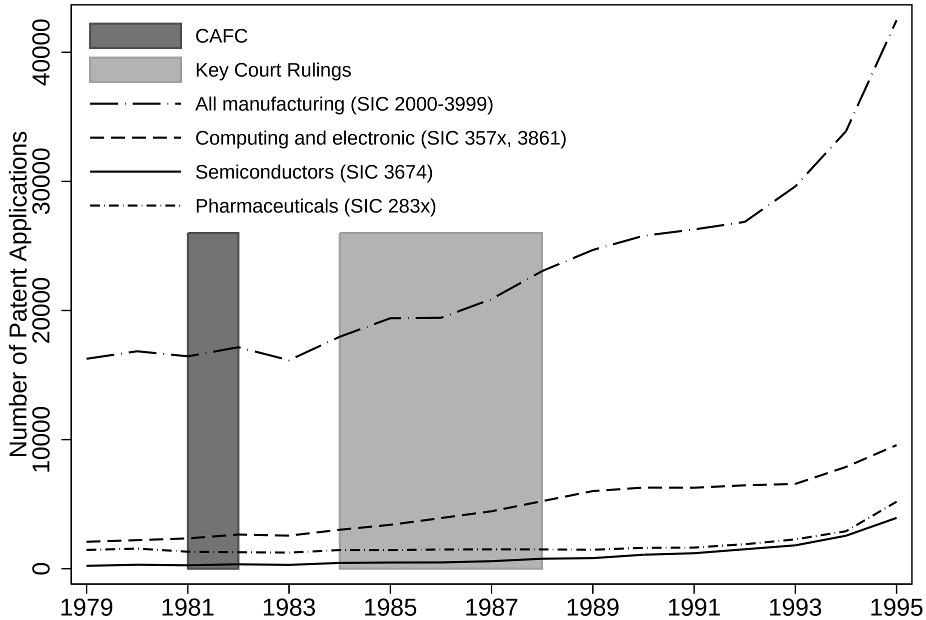
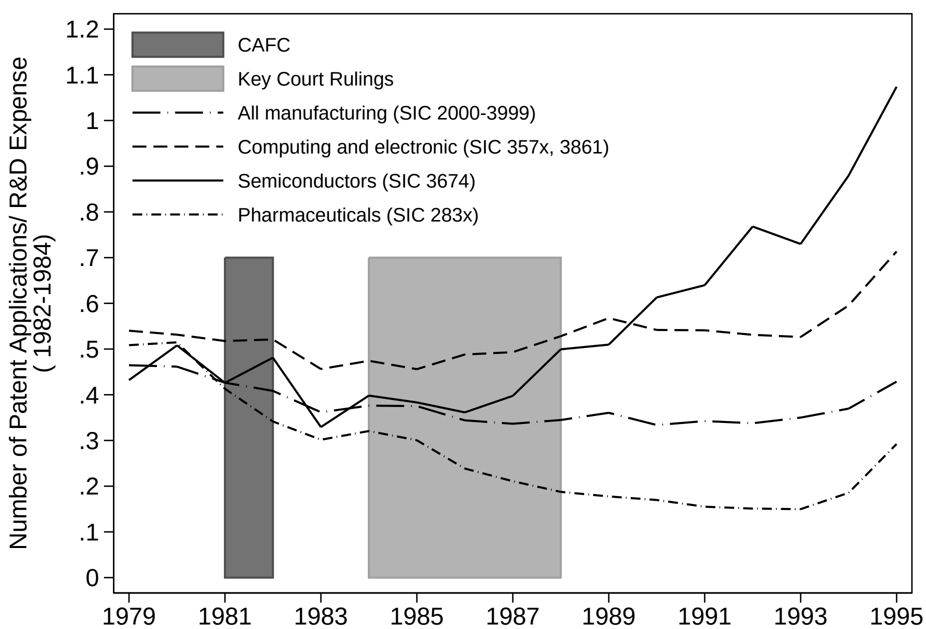


Figure 2 compares firm patent propensity across time and industry, where I define patent propensity as the ratio of patent applications to millions of dollars spent on R&D.

Figure 2: **Comparing Patent Propensity Across Industries**



Semiconductor firms have become increasingly active in patenting their inventions, especially relative to other industries.[5] It is further instructional to note the sharp increase in patent applications around the 1982 creation of the CAFC. The increase may indicate firms decision to patent previous trade secrets, while the subsequent dip may represent a return to trend. As with overall patenting, the increased propensity to patent occurs during or after the pro-patent judgements.

Hall and Ziedonis (2001) document that large and small firms use patents differently in this industry. Since industry innovations are fast-paced, patents prove a crucial component towards enabling IDM firms like Intel to introduce its newest line of microprocessors quickly. Hence, they generate large patent portfolios to insulate them from the risk of becoming bogged down in infringement litigation down the line. Fabless firms, on the other hand, use patents to secure "secure strong, 'bulletproof' proprietary rights to technologies in niche product markets."[6] Patents, therefore, can provide the sales and/or licensing revenue to overcome fixed costs of entry and to continue product development.

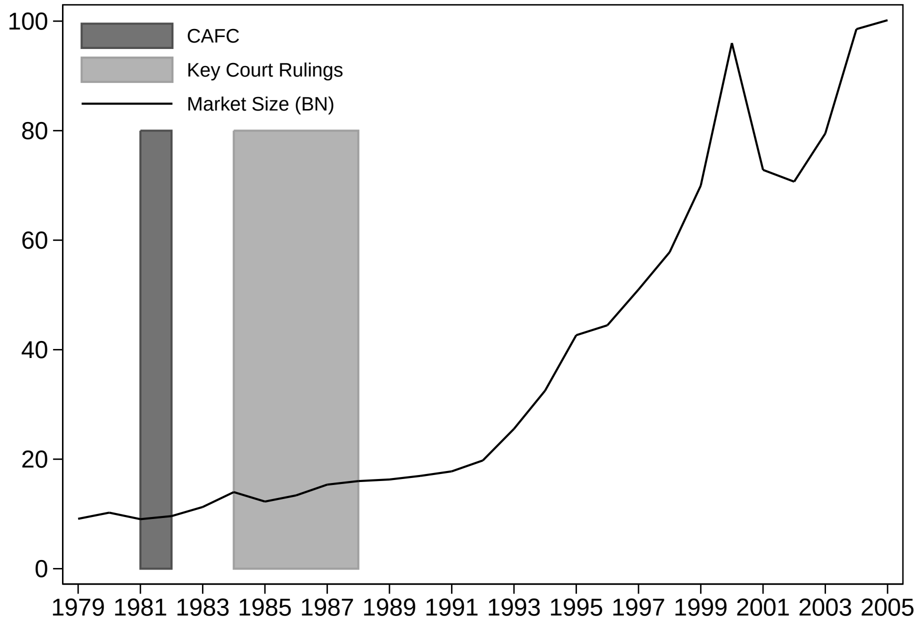
E. The Market has Grown

The explosion in spending on IT infrastructure and personal computing led to substantial growth over the last thirty years. Figure 3 illustrates this growth where I define market size as total revenue generated by firms whose principal line of business is "Semiconductors and Related Devices" (SIC 3674).

[5] This graph is similar to Hall and Ziedonis (2001), who focus on patent grants rather than applications. Since I'm interested in firm's decisions whether or not to patent an innovation, using applications (and the year the application is made) seems more appropriate.

[6] Page 110, Hall and Ziedonis (2001)

Figure 3: **Market Size Across Time**



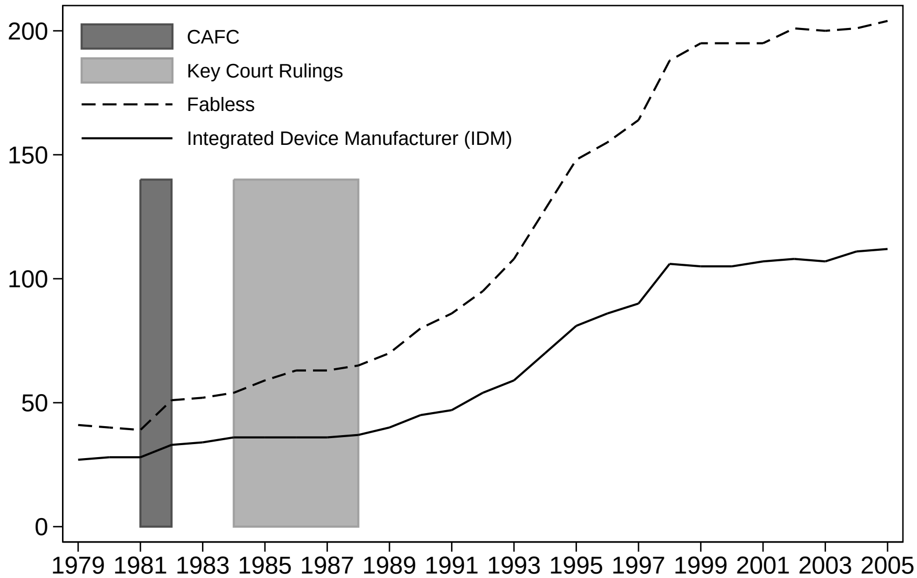
The substantial increase in slope represents an increase in the annual real growth rate from 6.6% in the 1980s to 16.1% the in 1990s.

F. Market Structure has Changed

As mentioned earlier, there are there are fundamentally two different kinds of semiconductor firms. The first group consists of integrated device manufacturers (IDMs) which are vertically-integrated, meaning they designed the product, fabricated the product, and sell the product. The second group is comprised of firms focused on designing next generation technologies and selling/ licensing these technologies or outsourcing production to the fabrication firms. Since they lack any kind of production/ fabrication abilities, these firms are referred to as "fabless."

Figure 4 illustrates the sharp increase in the number of IDM and fabless firms in the industry following both the change in patent protection and the increase in demand.

Figure 4: **Firm Composition over Time**



During the 1980s 37% of firms were considered fabless. This number grew to 46% during the 1990s and has remained roughly constant since. Table 2 documents this shift along other metrics.

Table 2: US Semiconductor Industry Descriptive Statistics

	1985-1989		1990-2000		2000-2005	
Variable (Average Firm)	IDM	Fabless	IDM	Fabless	IDM	Fabless
Number of firms (N)	34.5	21.8	80.6	65.7	108.4	91.0
Sales ($MM)	292.9	142.0	385.7	220.4	494.3	445.8
- YOY Growth Rate (%)	16.2	38.8	42.8	92.3	45.9	33.6
Net Income ($MM)	13.8	0.9	45.8	18.3	-81.0	-21.1
R&D Expense / Sales	0.16	0.50	0.58	0.24	2.35	1.08
Patent Apps/ R&D Expense	0.45	0.36	0.83	1.29	-	-
% Increasing Revenue	68.0	70.4	73.4	77.3	66.4	71.4
% Increasing Patents	43.6	50.9	50.2	58.0	-	-
Exit Rate (%)	3.7	3.6	3.3	3.3	3.8	3.8
Market Size ($BN)	12.9		42.8		86.3	

Note: Reliable patenting data only extends to 2000

Table 2 illustrates rapid growth during the 1990s. Presumably fueled by positive demand shocks related to the IT boom, overall market size, sales, and net income increased dramatically. Increased entry and stable exit rates led to decreased market shares. Concurrent to this growth is an increase in average patenting as patent applications per $million R&D increased from 0.36 to 1.29.

The post-2000 industry appears to have stabilized, as revenue growth rates dropped to near 1979-1989 levels and entry rates decreased significantly. The negative mean net income number is presumably due to large operating losses and subsequent write-offs incurred during the 2001 recession. The current industry appears to be characterized by a large number of firms with little to no dominant market share. While I don't have reliable patenting data past 2000, aggregate patenting figures[7] suggest that firm patenting behavior has, at the very least, not decreased.

4 Model

The model is similar to Ericson and Pakes (1995). Firms are heterogeneous in their productivity level x with discrete support $X = [1, \overline{x}]$ and patent stock k with discrete support $K = [1, \overline{k}]$. Firms earn profit by producing and selling a product, but they may also earn licensing revenue. Firms choose how much R&D to conduct, how much to spend on licensing others' ideas, and whether to adjust the patent stock. High levels of patent protection require the firm to license competitors' technologies, hence increasing its licensing expense. Total market licensing revenue is endogenous in the model and is a function of the level of protection. A firm's licensing revenue is related to its share of patents in the industry. Both production and licensing profits are simple functions of the aggregate state thereby simplifying strategic interactions amongst firms and focusing the analysis on the differential effects of patent protection and market size.

4.0.1 Segmenting the Market

Authors have argued that the increase in patent protection drove the the bifurcation of the US semiconductor industry into traditional fabrication-based (e.g., Intel) and fabless firms. I allow for this segmentation by introducing fabless firms into the market. Similar to traditional firms, fabless firms can conduct R&D (ι) and spend money increasing their patent stock (χ). These firms do not, however, produce goods themselves. Hence, they earn zero production profit and instead rely on licensing revenue. Define the state variable $j \in \{d, p\}$ as an indicator variable, where $j = d$ ($j = p$) implies the firm operates a design (production) plant.

4.0.2 Patent Protection

The level of patent protection is denoted $\gamma \in [0, 1]$ and captures the share of production-related profits the firm must pay for licensed technologies. One should view γ as influencing the royalty payment that fabrication firms (e.g., Intel) pay other firms (both traditional and fabless) for use of a patented idea. As γ increases, traditional firms are required to pay more for using others' ideas.

[7] see Jaffe and Lerner (2004)

4.0.3 Profit and Licensing Functions

There exists L representative agents in each period t, each endowed with a unit of time. The agents value the discounted present value of a set of differentiated goods using Cobb-Douglas preferences:

$$U_t = \sum_{t=0}^{\infty} \beta^t C_t \tag{1}$$
$$C_t = \left[\int_{i \in I} q_{i,t}^{\alpha}\right]^{\frac{1}{\alpha}}$$
$$\alpha \in (0,1)$$

where i denotes a product variety and I is the set of all product varieties. This set-up implies that the demand for firm i's good is:

$$q_{i,t} = \frac{p_{i,t}^{-\epsilon}}{P_t^{1-\epsilon}} \cdot M_t$$
$$\epsilon = 1/(1-\alpha)$$

where ϵ is the elasticity of substitution between differentiated goods and M_t is aggregate spending on differentiated goods (ie, the size of the market). P_t is the price index for the economy in period t, defined as:

$$P_t = \left[\int_{i \in I} p_{i,t}^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$$

Fabless firms do not produce output, while traditional fabrication firms produce goods using only labor (l). The economy supplies labor inelastically at wage rate w_t. All firms are heterogeneous in unit labor productivity (x) using the following linear supply function

$$q_{i,t} = x_{i,t} \cdot l_{i,t}$$

where productivity levels x lie in the compact set X.

Both traditional and fabless firms also generate revenue via licensing. Licensing revenue depends on the stock of patents (k) held by the company. Patents do not affect spot market production. Similar to productivity, I assume k lies in a compact set K. Define total licensing revenue as (M^L), which is an endogenous object. I assume any existing patents are equally valuable to all firms and that firms are matched with ideas to license uniformly.[8] Define licensing revenue for a firm i with productivity x and patent stock k as η, where

[8] Alternative mechanisms would be to create a matching function in which firms prefer to license ideas from firms either close to

η is proportional to the firm's productivity-weighted share of total industry patents

$$\eta_{i,t}(x,k) = M_t^L \cdot \frac{x_i \cdot k_i}{\int_{h \in I} x_h k_h} \tag{2}$$

This set-up embeds an important insight that all patents are not created equal. The patent stock of higher productivity firms will have higher value than lower productivity firms. Hence, both traditional and fabless firms can increase their licensing revenue by conducting R&D and improving their productivity state.

Since firms enter symmetrically into equation (1) and are differentiated only by their segment and level of productivity and patent stock. Henceforth, I will refer to "firm (j, x, k)" rather than "firm i." I can then rewrite the price index as

$$P_t(\mu) = \left[\sum_{j=d,p} 1_{\{j=p\}} \int_{x \in X} \int_{k \in K} p_t(x)^{1-\epsilon} \mu_t(j,x,k) \right]^{\frac{1}{1-\epsilon}}$$

where $\mu_t(j, x, k)$ is the mass of segment j firms with productivity level x and patent stock k. I assume the cardinality of X is large enough (ie, there exists a large enough number of firm types) to imply non-strategic pricing behavior, hence $p_t(x)$ is the standard constant mark-up pricing equation: $p_{i,t}(x) = \frac{w}{\alpha} \cdot \frac{1}{x}$.

Price competition occurs in a spot market, hence pricing behavior and profits are determined given the distribution of firms (μ_t). Using consumer demand, firm production, and the pricing equation outlined above, firm profit is

$$\pi_t(x, \mu|\gamma) = x^{\epsilon-1} \cdot (1-\gamma)(1-\alpha) \left(\frac{w_t}{\alpha P_t} \right)^{1-\epsilon} M_t$$

where the dependence of the price index on μ is implied. Profit is increasing the market size (M_t), firm productivity level (x), and competitor prices (via the price index), while decreasing in the level of patent protection (γ).

Total licensing revenue in the industry is

$$M_t^L = \gamma M_t (1-\alpha) \left(\frac{w}{\alpha P_t} \right)^{1-\epsilon} \sum_{j=d,p} \int_x \int_k \mu_t(j,x,k) x^{\epsilon-1}$$

which is increasing in both the level of patent protection (γ) and market size (M_t).

their level of productivity (the patented ideas may be more relevant/ implementable) or from firms close to the technological frontier (the patented ideas may be more "cutting-edge").

Equilibrium Definition: Given state μ, a spot market equilibrium is a set of

1. Demand functions:

$$q_t(x,\mu) = \frac{p_t(x)^{-\epsilon}}{P_t^{1-\epsilon}} \cdot M_t$$

2. Price functions:

$$p_t(x) = \frac{w_t}{\alpha \cdot x}$$

3. Profit functions:

$$\pi_t(x,\mu) = x^{\epsilon-1} \cdot (1-\alpha) \left(\frac{w_t}{\alpha P(\mu)} \right)^{1-\epsilon} (1-\gamma) M_t$$

4. Firm license revenue functions:

$$\eta_t(j,x,k) = \frac{xk \cdot M_t^L}{\sum_j \int_{x'} \int_{k'} \mu_t(j,x',k')}$$

Such that the licensing market clears

$$\sum_{j=d,p} \int_x \int_k \eta_t(j,x,k)\mu_t(j,x,k) = \gamma M_t (1-\alpha) \left(\frac{w}{\alpha P_t} \right)^{1-\epsilon} \sum_{j=d,p} \int_x \int_k \mu_t(j,x,k) x^{\epsilon-1}$$

4.0.4 Firm Dynamics

Incumbent firms enter the period with state (x, k). Production firms earn both profit and licensing revenue, while fabless firms earn only licensing revenue. All incumbent firms may choose whether or not to exit the industry. I endogenize exit using the following mechanism. Each period incumbent firms observe an idiosyncratic "sell-off" value $\phi \sim \Phi$. The value of ϕ is private information. Both traditional and fabless firms draw their sell-off values from the same distribution, which is iid across firms and time. An exiting firm is one whose ϕ is greater than the discounted value of remaining in the industry. The exiting firm enters the period, earns profit and licensing revenue, earns the sell-off value, and exits permanently.[9]

All continuing firms make two decisions. First, they choose how much labor to hire for R&D (ι). Productivity draws follow the probability function $F(x_{t+1}|x_t, \iota)$, where $F(\cdot)$ is increasing in both conditional arguments. Second, incumbent firms spend χ to adjust their stock of patents, after the outcome of R&D is known.

[9] Doraszelski and Satterthwaite (2009) show incorporation of idiosyncratic, privately-known sell-off values is an important ingredient to guarantee existence of a Markov-Perfect equilibrium in this class of model.

This set-up allows firms to spend different amounts of money towards gaining patent approval.[10] Similar to the R&D process, I model the patent process using the probability function $H(k_{t+1}|k_t, \chi)$, where $H(\cdot)$ is increasing in both conditional arguments. Note a one-period lag between application and grant - applications made today are granted by the USPTO next period.

I also allow for firm entry. Entering firms pay a one-time fixed cost $f^j_{e,t}$, then draw initial productivity from a time-invariant distribution G^j_t. Firms enter the industry if, and only if, the expected discounted value is greater than $f^j_{e,t}$.

4.0.5 Timing

Events occur in the following order:

1. Incumbent firms enter with state (x_t, k_t, μ_t)
2. Incumbent firms observe their sell-off values ϕ
3. Firms simultaneously set prices, earn profits, and pay/ receive licensing fees
4. Exit and entry occur
5. Incumbent firms invest in R&D
6. Research outcomes observed (x_{t+1})
7. Firms decide how much money to spend on increasing their patent stock (χ)
8. Next period's patent stock is realized (k_{t+1})
9. State space moves to $(x_{t+1}, k_{t+1}, \mu_{t+1})$

4.1 Incumbent Firms

Define $\mathcal{S}$ as the set of all decision rules with element $\sigma \in \mathcal{S}$. Consider an individual a segment j firm with productivity x and patent stock k. The firms takes its individual state (x, k) and the aggregate state μ as

[10] For example, a firm can choose to hire a top tier patent attorney.

given and solves the following recursive maximization problem:

$$V^j(\phi, x, k, \mu) = 1_{\{j=p\}}\pi(x, \mu|\gamma) + \eta(x, k, \mu|\gamma) + \max\{\rho^j(x, k, \mu), \phi\} \quad (3)$$

$$\rho^j(x, k, \mu) = \max_{\iota} \left\{-\iota \cdot w + E_{F(x'|x,\iota)} \left[v^j(x', k, \mu)\right]\right\} \quad (4)$$

$$v^j(x', k, \mu) = \max_{\chi} \left\{-\chi \cdot w + \left[\frac{1}{1+r}\right] E_{H(k'|k,\chi),\Phi} V^j(\phi', x', k', \mu')\right\} \quad (5)$$

subject to

$$\mu' = \Upsilon(\mu; \sigma_i, \sigma_{-i})$$

where $\sigma_{x,k} \in \mathcal{S}$ and $\sigma_{-x,-k} \in \mathcal{S}$ are the decision rule(s) of firms at states x, k and $-x, -k$, respectively. All firms earn π and η in spot markets. Then, it decides whether to stay in the market and earn expected discounted profits ρ or sell its operations and earn ϕ. Third, it decides how much to invest in R&D (ι). Finally, the firm decides how many patents to have in the next period (k').[11] Given the outcome of the firm decision rules in the industry, the distribution of firms evolves according to $\Upsilon : \mu(x, k) \to \mu(x', k')$. All firms take the interest rate r as given.

4.2 Entering Firms

Prospective entrants take the aggregate state μ and the law of motion Υ as given and enter if, and only if, the expected discounted profits are greater than the cost.

$$f_e^j \leq \left[\frac{1}{1+r}\right] \int_{x'} \int_{k'} \int_{s'} V^j(s', x', k', \mu') d\Phi(s) dG_t^j(x', k') \quad (6)$$

$$\mu' = \Upsilon(\mu; \sigma_i, \sigma_{-i})$$

where G^j and f_e^j are the time-invariant initial distribution and entry cost in segment j, respectively. Free-entry implies (6) holds with equality in equilibrium. I also assume that firms may not switch between traditional and fabless segments.[12] Define $e^j(\mu)$ as the entry decision rule and assume there exist N^j potential entrants for both segments.

Proposition 1 *Given the number of prospective entrants N^j is sufficiently large and that prospective entrants play mixed strategy, entering with positive probability; then firm entry follows a Poisson random variable. Moreover, there exists a cut-off mass of entering firms (e^j) such that equation (6) holds with*

[11] I implicitly assume that the firm may choose to increase its patent stock even if R&D is not successful. This assumption is founded on the idea that firms often patent ideas/ technologies which they fail to commercialize.

[12] This is largely true in the data, though there are instances where traditional fabrication firms have adopted the fabless business model and vice-versa.

equality.

See appendix for proof.

4.3 Markov-Perfect Equilibrium

I restrict the action space to pay-off relevant strategies and use the notion of a Markov-Perfect equilibrium.

Definition- For every μ, a *Markov-Perfect Equilibrium* (MPE) is a set of decision rules $\sigma^j = (\rho^j, \iota^j, \chi^j, e^j\}$ such that

1. ρ^j satisfies equation (3) - firm continuation
2. ι^j satisfy equation (4) - investment
3. χ^j satisfies equation (5) - patenting
4. e^j satisfies equation (6) - firm entry
5. $\Upsilon(\mu, \sigma)$ is given by

$$\mu^j(x', k') = \int_x \int_k \Phi(\rho^j) F(x'|x, \iota^j) H(k'|k, \chi^j) \mu^j(x, k) + dG^j(x', k') e^j$$

6. Firm strategies are optimal

$$\sup_{\sigma_i \in \mathcal{S}} V^j(\phi, x, k, \mu | \sigma_i, \sigma_{-i}) = V^j(\phi, x, k, \mu | \sigma) \;\; \forall\, x \in X,\; k \in K,\; j = \{d, p\},\; \text{and } \mu \in \mathcal{M}$$

The final condition guarantees that there does not exist an optimal deviation.

5 Structural Estimation

Recall that this paper asks how much of the increase in entry of fabless firms is due to changing patent regulation. Answering this question requires modeling the US semiconductor industry we see in the data, as well as a hypothetical world without a change in patent protection. This section is devoted to addressing the first part.

5.1 Approximating the Markov Perfect Equilibrium

As noted by numerous authors, solving the problem above is computationally intensive (or impossible) for industries with a large number of firms (e.g., $N > 5$) or a large state space (e.g., 100 points). I remedy the *curse of dimensionality* by assuming firms are "boundedly rational," making decisions according to the long-run expected state. I approximate the MPE with the equilibrium concept developed by Weintraub, Benkard, and Van Roy (2008). The idea is that firms make decisions based on their beliefs pertaining to the firm distribution. These actions generate a long-run expected distribution of firms. In equilibrium, firm actions and the resulting distribution are consistent.

This approximation method is appropriate here because the model's Dixit-Stiglitz preferences and licensing revenue function limit strategic interactions amongst firms. Hence, all firms consider themselves "small" and do not internalize their effect on the aggregate state by construction. Further, recall that the question posed in this paper is to ascertain the relative importance of increased patent protection to the substantial increase in small firms. The exercise will be to first estimate parameters for the benchmark economy (i.e., the one we observe). I then perform a counterfactual to see how market entry, R&D, and patenting decisions change are affected to changes in market size and patent protection independent of the other. Since I approximate the MPE in both the benchmark and the counterfactual, I feel that any biases will be mitigated.

5.2 Parameterization

The model presented depends on specifications for distributions $\{F, G, H, \Phi\}$ and parameters $\{\epsilon, \beta, r, w, \gamma, f_e^j, \overline{x}, \overline{k}\}$[13]. I'll close many of these by imposing the following structure.

5.2.1 Transition Probabilities

I now assume the following forms for transition functions F, G, H, and Φ.

1. The productivity transition function, F, is stochastic and maps firm productivity x to x' conditional on the level of R&D effort (ι). Since the state space for productivity is discrete, I follow Ericson and Pakes (1995) and assume F takes the following form:

$$F(x'|x,\iota) = \begin{cases} \frac{(1-\delta_x)\iota}{1+\iota}, & x' = x + \Delta_x \\ \frac{1-\delta_x+\delta_x\iota}{1+\iota}, & x' = x \\ \frac{\delta_x}{1+\iota}, & x' = x - \Delta_x \end{cases}$$

[13] Note that I've excluded α (the heterogeneous good coefficient) since the model implies a 1-1 mapping between α and ϵ. Namely, $\alpha = \frac{\epsilon-1}{\epsilon}$

This construction implicitly defines the state space relative to an outside good. The term δ_x captures the exogenous probability that that the "value" of the outside good increases, hence making all goods in this industry less desirable. This decrease in desirability is modeled by a decrease in every firm's productivity. As others have noted, the value of δ_x identifies the rate of aggregate productivity growth in the industry.

2. The patent transition function (H) is also stochastic and has similar form, where firms spend χ dollars to increase their patent stock.

$$H(k'|k,\chi) = \begin{cases} \frac{(1-\delta_k)\chi}{1+\chi}, & k' = k + \Delta_k \\ \\ \frac{1-\delta_k+\delta_k\chi}{1+\chi}, & k' = k \\ \\ \frac{\delta_k}{1+\chi}, & k' = k - \Delta_k \end{cases}$$

The term δ_k captures the exogenous probability that some of the firm's patents expire and the stock decreases.

3. I restrict the entry distribution to be time-invariant and identical between fabless and production firms ($G_t^j = G$). This simplifying assumption is required since I lack financial information on fabless firms to estimate G^0. The initial productivity draw follows a Pareto distribution with shape parameter equal to one, while all firms enter market with one patent.

4. Similar to Weintraub, Benkard, and Van Roy (2008), the distribution of idiosyncratic firm sell-off values (Φ) is assumed exponential with parameter (κ).

In total, these specifications introduce three new parameters: $\{\delta_x, \delta_k, \kappa\}$.

5.2.2 Fixed Costs

For simplicity, I restrict the fixed costs to be time-invariant. While I can pin down the fixed entry cost for traditional firms using observed Compustat entry rates, there is less information on fabless firms. To remedy this issue, I introduce the entry mass of fabless firms e^0 as an unknown parameter.

5.2.3 Other Parameters

For simplicity, I normalize the wage rate to one. The model predicts constant mark-up equal to w/α. Given wage rate equal to one, I computed average income margin[14] in the Compustat data set equal to 0.22 which implies $\alpha = 0.78$. The elasticity of substitution ϵ is then pinned down using $\epsilon = \frac{1}{1-\alpha}$ (4.54). I calibrated the discount rate using the long-run rate of return of 7% on federal bonds (i.e., r=0.07), therefore $\beta = \frac{1}{1.07}$.

5.3 Solving the Model

Define the expected long-run firm distribution as $\tilde{\mu}$. Solving the model follows these steps:

1. Guess a value for the long-run expected firm distribution. Call this $\tilde{\mu}^0$.
2. Compute profit and licensing revenue
3. Compute equilibrium firm decision rules ι, χ and value functions V, ρ, v
4. Given firm decision rules, generate a new guess for the long-run expected firm distribution. Call this $\tilde{\mu}^1$
5. Stop if $\| \tilde{\mu}^1 - \tilde{\mu}^0 \|_\infty$ is sufficiently small. Otherwise, set $\tilde{\mu}^0 = \tilde{\mu}^1$ and return to (1)

5.4 Estimation Approach

Define the remaining parameters as $\Theta = \{\gamma, \delta_x, \delta_k.\kappa, \overline{x}, \overline{k}, e^0\}$ which I pin-down by jointly estimating Θ using a simulated method of moments approach. That is, I construct data moments using firm-level financial and patent data from Compustat and the NBER Patent Citation databases.[15] Compustat data indicates the existence of two steady states: 1979-1989 and 2000-2007. Unfortunately, the NBER patent database can reliably cover only up to 1995. I remedy this shortcoming by matching patent propensity rates during the observed transition path. Consequently, the estimation requires solving the two steady-states and the corresponding transition path. This approach yields parameter estimates for each steady-state.

For each estimation, I choose Θ to solve

$$\hat{\theta} = \underset{\Theta}{\text{argmin}}[M'_\Theta W M_\Theta] \tag{7}$$

[14] Where income is defined as earnings before interest, taxes, depreciation, and amortization (EBITDA). This income measure is closely related to profits in the model.

[15] See appendix for further details

where

$$
\begin{aligned}
M_{\Theta} &= \begin{bmatrix} M_1^d - \frac{1}{N_s}\sum_{s=1}^{N_s} M_1^m(\hat{\Theta}) \\ \vdots \\ M_J^d - \frac{1}{N_s}\sum_{s=1}^{N_s} M_J^m(\hat{\Theta}) \end{bmatrix} \\
M^d &\equiv \text{data moment vector} \\
\Omega^{-1} &\equiv \text{weight matrix}
\end{aligned}
$$

Where J is the number of moments and W is the positive, semi-definite optimal weight matrix which guarantees the existence of a minimal value. Further, I compute W by first computing the variance-covariance matrix Ω of the data moments using a bootstrap method with replacement and set $W = \Omega^{-1}$. Equation 7 is highly non-linear which makes finding a global minimum difficult. I mitigate this issue by searching for $\hat{\Theta}$ using a simulated annealing minimization algorithm to limit the risk of falling into local minima.

5.5 Moments and Identification

Firms spend more on licensing and invest more on developing patents as the patent protection factor (γ) increases, hence increases in γ lead to increases in patents/R&D. The stochastic depreciation rates (δ_x, δ_k) and support upper-bounds ($\overline{x}, \overline{k}$) affect firm advancement within the industry. Following Yu (2008), I identify these using the % of firms increasing in revenue and patent stock, respectively. The sell-off parameter (κ) influences the probability a firm exits the industry and is identified with the industry exit rate. I add to this set of moments the ratio of R&D expense to sales (i.e., R&D intensity). Observations in the top and bottom 2.5 percentile (with respect to revenue) were dropped to mitigate outlier effects. Since the actions of firms vary according to the state in both the data and the model, I also compute moments for firms above and below median revenue.

5.6 Estimation 1: the First Steady State

I first fit the model to moments for the years 1985-1989. I chose to use 1985 as the beginning year to avoid any influences of the 1981-1982 US recession. Since industry data indicates limited activity of fabless firms in this steady-state, I assume that the fixed cost of entry f_e^0 is sufficiently high to guarantee zero entry of fabless firms.

5.6.1 Results

Table 5.6.1 presents the results for the first estimation.

Table 3: Estimation 1 Results

Variable	Estimate	SE
γ	0.42	0.048
δ_x	0.38	0.045
$\overline{x}$	1.18	0.029
δ_k	0.47	0.056
$\overline{k}$	12.11	0.565
κ	701.54	72.09

Standard errors were computed using a numerical approximation to the Jacobian at the given point estimates. Table 4 presents the targeted and untargeted moments.

Table 4: Testing the Model (1985-1989)

	Industry		<Median		>Median	
	Data	Model	Data	Model	Data	Model
Avg Revenue ($MM)	321.5	250.1	23.1	199.5	625.1	327.8
Herfindahl-Hirschman Index (HHI)	0.136	0.024	-	-	-	-
% inc revenue	65.30	62.00	65.50*	57.10	65.00*	56.10
% inc patents	79.20	72.10	91.60*	75.80	66.70*	61.50
Avg research/ revenue	0.109	0.080	0.101*	0.090	0.116*	0.070
Patents granted/ $ research	0.300*	0.300	0.450	0.320	0.290	0.290
Exit rate	0.017	0.048	0.017*	0.066	0.017	0.020

* Denotes targeted moment

By construction, the model matches most of the targeted moments well. Of particular importance is the fact the model generates patenting ratios largely consistent with the data. Along with the low error on the IPR protection term γ suggests a high degree of sensitivity in the model to changing IPR policies. In comparison, the model replicates the data poorly for average ratio research expense to revenue despite being a targeted moment. Also, the model generates less market concentration and more exit than observed in the data.

5.7 Estimation 2

Computing the second stage is more involved, so I simplify the estimation by trimming Θ to $\{\gamma, \kappa, \overline{k}, e^0\}$ and use the point estimates recovered from the first estimation for δ_x, δ_k and $\overline{x}$. The matched patent-Compustat file reliably extends through 1995. That means I can't compute the ratio of patents to R&D in the second steady state, but I can compute it during the transition path (1990-1995). I use the average ratio of patents to R&D and the average % of firms increasing their patent stock during the transition path to identify γ and $\overline{x}$, respectively.

In order to compute the transition path, I first have to compute the second steady state using the guess for Θ and industry market size. I then compute the transition path using backwards induction similar to Weintraub, Jeziorski, Benkard, and Van Roy (2008). I also use the ratio of fabless firms to traditional firms to identify the fabless firms entry rate e^0. The remaining identifying moments are the same as in the first estimation.

5.7.1 Results

Point estimates are reported in table 5.

Table 5: Estimation 2 Results

Variable	Estimate	SE
γ	0.91	0.002
κ	355.06	7.459
$\overline{k}$	15.18	0.195
e^0	66.15	0.233

The IPR parameter γ increased substantially from the first steady-state, while κ decreased by 50%. The latter reflects a decrease in the outside option and a subsequent decrease in the exit rate. Table 6 presents the targeted and untargeted moments.

Table 6: Testing the Model (1990-2005)

	Industry		<Median		>Median	
	Data	Model	Data	Model	Data	Model
Avg Revenue ($MM)	509.6	224.5	55.00	176.4	969.6	278.6
Herfindahl-Hirschman Index (HHI)	0.071	0.027	-	-	-	-
% inc revenue	64.20	57.90	65.80*	59.00	62.60	51.50
% inc patents	62.20*	88.90	-	-	-	-
Avg research/ revenue	0.156	0.080	0.162	0.100	0.151	0.070
Patents granted/ $ research	0.581*	0.401	-	-	-	-
Ratio of firms	7.045*	7.046	-	-	-	-
Exit rate	0.025	0.022	0.039*	0.039	0.012	0.006

* Denotes targeted moment

As with the first estimation, the model generates too little market concentration and too much exit. Table 7 presents the patenting intensity and growth moments for the transition path between steady states.

Table 7: Transition Path

	Patents granted/ $ research		% inc patents	
Year	Data	Model	Data	Model
1990	0.286	0.418	0.564	0.892
1991	0.330	0.406	0.613	0.892
1992	0.442	0.397	0.597	0.892
1993	0.413	0.392	0.662	0.891
1994	0.599	0.391	0.707	0.888
1995	0.531	0.399	0.770	0.882

6 Counterfactual Exercises

The parameter estimates from Sections 5.6 and 5.7 and their implied industry equilibria generate similar industry statistics as those seen in the data. Hence, they provide a control environment for my counterfactual experiments.

The next step is to find the relative contribution of a change in patent policy towards changing market structure. The idea is similar to a comparative statics exercise in which one explores the relative effects of a set of parameters by varying each while holding the others constant. The parameters of interest in these exercises are the protection policy (γ) and the market size (M).

Specifically, I run two counterfactual experiments. First, I solve the steady-state equilibrium assuming the industry did experience a demand shock, but patent protection did not change. Second, I resolve the steady-state equilibrium assuming the converse. Table 8 presents the results:

Table 8: Counterfactual Results

	Benchmark	Experiment 1	Experiment 2
Avg Revenue ($MM)	224.5	288.5	277.1
Research/ revenue	-	-	-
- Average	0.008	0.008	0.008
- Median	0.008	0.009	0.010
Patents granted/ $ research	0.404	0.397	0.403
% increasing revenue	57.90	55.60	55.10
% increasing patents	59.70	62.60	62.10
Herfindahl-Hirschman Index (HHI)	0.027	0.006	0.171
Exit Rate	0.022	0.014	0.013
Ratio of firms	7.046	1.577	75.746
IPR protection (γ)	0.91	0.42	0.91
Market size ($BN)	95.7	95.7	19.4

Note: The statistics for "patents granted/ $ research" and "% of firms increasing patents" values are based on the steady-state.

The two counterfactual exercises indicate that the change in IPR policy had the largest impact on firm composition. Returning the IPR policy pre-CAFC levels led to a significant decrease in the HHI as the composition of firms shifts from fabless to traditional production firms. Average revenue increases reflecting a shifting of cash-flow from licensing to production. Interestingly, patent intensity only falls slightly, while the percent of firms increasing their productivity level and patent stock both increase.

Decreasing market demand to 1980s levels had an even larger effect on the composition. Firm composition shifts dramatically away from fabless firms leading to a much higher market concentration amongst traditional production firms. As with the first experiment, the percent of firms increasing their productivity level and patent stock both increase. Patent intensity increases slightly, likely reflecting the increased return to patenting.

7 Conclusion

The data indicates a clear shift in the US semiconductor industry during the 1990s. A previously consolidated industry composed of vertically-integrated firms became a fragmented industry of both traditional production and specialized "fabless" firms. At the same time firm patent propensity increased sharply. Others have hypothesized that the legal strengthening of US patent protection in the 1980s is responsible for both the shift in patenting and the change in market structure. In this paper I asked how much of the change in market structure is due to patent reform vis-à-vis changes in market demand. I constructed a structural model in which semiconductor firms choose both R&D and patenting effort. In the model, increases in demand and patent protection are both capable of increasing the stock of fabless firms. I estimated the key parameters of the model using a simulated method of moments approach. To answer my question, I conducted two counterfactual experiments to isolate the effects of changing patent protection and demand. The results indicate that while the shift in protection did affect firm patenting and licensing behavior, the majority of the shift in market structure is demand-driven.

Of course, the paper's results are a function of my assumptions regarding competition within the market, the R&D process, and licensing revenue. While I've attempted to make conservative assumptions and stay consistent with the literature where possible, there is room for improvement. For example, modifying the R&D process to account for firm spillovers may increase the effect of fabless firms and increase the market effect of increased patent protection.

References

Berry, S., J. Levinshon, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

Boldrin, M., and D. K. Levin (2008): *Against intellectual monopoly*. Cambridge Press.

Doraszelski, U., and M. Satterthwaite (2009): "Computable Markov-Perfect Industry Dynamics," mimeo.

Ericson, R., and A. Pakes (1995): "Markov-perfect industry dynamics: a framework for empirical work," *Review of Economic Studies*, 62(1), 53–82.

Hall, B. H., and R. H. Ziedonis (2001): "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995," *RAND Journal of Economics*, 32(1), 101–28.

Hunt, R. (1996): "The Value of R&D in the U.S. Semiconductor Industry: What Happened in the 1980s?," mimeo.

——— (1999): "Patent Reform: A Mixed Blessing For the U.S. Economy?," *Federal Reserve Bank of Philadelphia: Busines Review*, pp. 15–29.

Jaffe, A. B., and J. Lerner (2004): *Innovation and its Discontents*. Princeton University Press.

Kortum, S., and J. Lerner (1998): "Stronger protection or technological revolution: what is behind the recent surge in patenting?," *Carnegie-Rochester Conference Series on Public Policy*, 48(1), 247–304.

Levin, R. C. (1982): "The Semiconductor Industry," in *Government and Technical Progress: A Cross-Industry Analysis (Pergamon*. Press.

Moore, G. (1965): "Cramming more components onto integrated circuits," *Electronics Magazine*, 38(8).

Organization, W. T. (1994): "Agreement On Trade-Related Aspects Of Intellectual Property Rights.," *The Uruguay Round Agreements*, pp. 319–351.

Standard & Poor's Compustat (1970-2000): http://wrds.wharton.upenn.edu/.

Taylor, C., and Z. Silbertson (1973): *The Economic Impact of the Patent System: A Study of the British Experience*. New York: Cambridge University Press.

Tilton, J. E. (1971): *International diffusion of technology; the case of semiconductors [by] John E. Tilton*. Brookings Institution Washington,.

United States Patent and Trademark Office (USPTO) (2007): www.uspto.gov.

von Hippel, E. (1988): *The Sources of Innovation*. Oxford University Press.

Weintraub, G. Y., C. L. Benkard, and B. Van Roy (2008): "Markov Perfect Industry Dynamics With Many Firms," *Econometrica*, 76(6), 1375–1411.

Weintraub, G. Y., P. Jeziorski, C. L. Benkard, and B. Van Roy (2008): "Nonstationary Oblivious Equilibrium," .

Yu, X. (2008): "A Structural Emprical Model of R&D, Firms Heterogeneity, and Industry Evolution," mimeo.

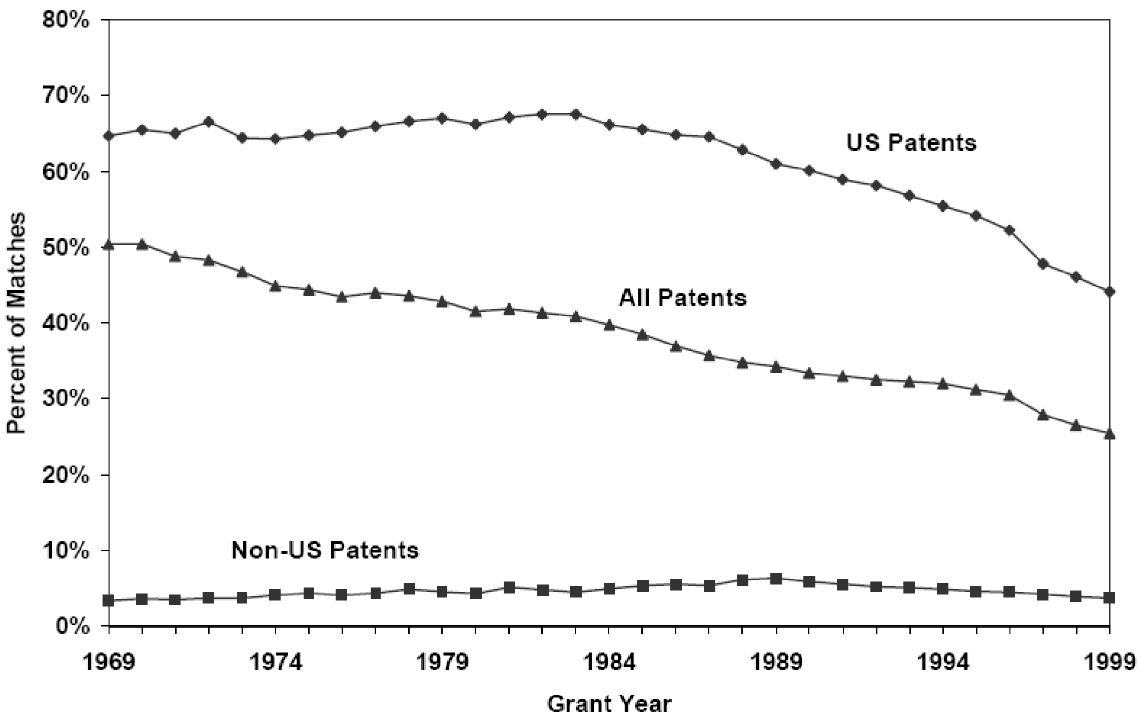
A Appendix

A.1 Data Sources

Since the focus of this paper is competition and innovation within the semiconductor industry, I isolated attention to publicly-traded firms whose principal business line is semiconductors and related devices (SIC3674). I used the NBER Patent Citation Database to compile a detailed collection of these firms' patenting efforts and matched the results with innovation-related financial information from Compustat.[16] The result is a fairly comprehensive sample of semiconductor firms, their propensity to patent, their financial performance, their R&D efforts, and their size.

The financial information is from Compustat, while the patent information is from the NBER *Patent Citation Data File*. Hall, Jaffe, and Trajtenberg matched patent grant data from the USPTO with Compustat CUSIP identification. The match was based on the assignee names in the USPTO data and the list of firm names in Compustat.

Figure 5: Compustat Match Rate



[16] Details regarding the data set are in the appendix.

The decreasing match rate in the latter part of the sample is largely due to the fact that the authors' used Compustat firms from 1989. The CUSIP provides unique identification with Compustat financial information, so the final data set is a list of all patent applications from 1970-1995 and the financial information associated with the assignee. The match is made using the application year-CUSIP combination. The following table presents some summary descriptive statistics of the semiconductor industry.

Table 9: Industry Descriptive Statistics (1970-1995)

Category	Variable	Mean	Standard Deviation	Maximum	Minimum
Financial Information	Number of Firms (pr year)	70.7	29.2	142	38
	Revenue ($MM)	324.2	1,178.3	16,202	0.0
	Market Share (%)	1.5	5.2	52.4	0.0
	Income ($MM)	25.4	170.0	3,566.0	-409.0
	Research ($MM)	33.1	104.9	1,269.0	0.0
	-Firms Reporting R&D (%)	99	1	100	98
	Plant, Property, & Equipment ($MM)	220.4	774.4	11,792	0.0
	Employees (000)	3.2	10.9	89.9	0.0
Patent Information	Number of Patenting Firms	59.5	18.1	102	36
	-Share (%)	87	8	95	72
	Patents (N)	38	90	758	1
	Patents/ R&D	1.79	6.1	65.4	0.0

*All dollar values are real (1982-1984 base)

A.2 Proofs

Proposition 1 *Firm entry follows a Poisson random variable. Moreover, there exists a cut-off mass of entering firms (e) such that* $\beta \cdot E[V(x', k', \mu')|G] = f_e$.

Proof I first show that entry follows a Poisson random variable. The proof follows Weintraub, Benkard, and Van Roy (2008). There are N potential entrants where N is assumed sufficiently large and each firm enters with the same probability p_N. Define $V_N(f)$ as the expected discounted profit flows for each entering firm if f firms enter simultaneously. By construction, $V_N(f)$ is decreasing in f. Free entry then implies the following equation must hold

$$\sum_{f=0}^{N-1} p_N^f (1-p_N)^{N-f-1} V_N(f+1) - f_e = 0 \tag{8}$$

for which there exists a unique solution $p_N^* \in (0,1)$ for each sufficiently large F, where I assume that N is sufficiently large such that an interior solution exists. Further, define $\lambda = \lim_{N\to\infty} N p_N^*$ and X_N as a binomial random variable with parameters (N, p_N^*). Then $\lim_{N\to\infty} X_N = Z$ where Z is a Poisson random variable with parameter λ.

So long as the number of potential entrants is sufficiently large and each potential entrant plays the same mixed entry strategy, then entry can be modeled as a Poisson random variable with expected entry λ. ■

A.3 About Intellectual Property Rights

The paper largely deals with "utility" patents[17]. Utility patents largely grant the holder

> the right to exclude others from making, using, offering for sale, or selling the invention... or importing... products made by that process (USPTO)

In exchange, the inventor makes his/ her invention public information. The state hopes this revelation enables others to learn from the invention, enhancing their own inventiveness, and leading to more productive innovations for the country at large. This revelation is actually quite a commitment since any patent application must

> disclose the invention in a manner sufficiently clear and complete for the invention to be carried out by a person skilled in the art (WTO)

The cost of this trade-off is particularly stark in the U.S. where patent applications become public information 180 days after submission.[18] Consequently, the firm may reveal its idea before even taking advantage of the idea itself, thereby enabling competitors to piggy-back on its R&D efforts.

[17] For example other forms of intellectual property right protection are copyrights and trademarks.

[18] The combination of a sharp increase in number, breadth, and complexity of patent applications, has inundated the USPTO. In response, it uses the input of the outside world to help verify the validity of patent claims. Ironically, the patent office is using the strategy of open-source software development to aid in its efforts.

B Computational Algorithm

In this section, I outline the computational algorithm used to solve for the OE and the POE. It is important to note that the equilibrium computed is a function of input parameters Θ, and that the remainder of the algorithm takes these as given.

The algorithm used is similar in methodology to Weintraub, Benkard, and Van Roy (2008). I begin with some introductory remarks and then proceed to outline the algorithm more systematically.

B.0.1 Useful Operators

Note that the distribution of firms $\mu \in \mathcal{M}$ is a measure on $(\mathbb{R}^2, \mathcal{B})$ where B is a Borel σ-algebra. Let $\mathcal{P}(\mathbb{R}^2)$ be the space of probability measures on $(\mathbb{R}^2, \mathcal{B})$ and define the operator $\Phi : \mathcal{P}(\mathbb{R}^2) \to \mathcal{P}(\mathbb{R}^2)$ as

$$(\Phi\mu)(x', k') = \sum_x \sum_k F(x'|x, I)G(k'|k, \chi)\mu(x, k) + F_e(x', k')e \tag{9}$$

Note that given stationary decision rules, one can use Φ to create a stationary distribution μ^{SS}. Firms will use this steady-state distribution as a forecast of the long-run industry average.

I solve for equilibrium entry using a contraction mapping similar to Berry, Levinshon, and Pakes (1995). Define the following operator

$$\begin{aligned} \Psi(\tilde{e}) &= \tilde{e} + \log(\text{EVF}) - \log(f_e), \text{ where} \quad (10) \\ \tilde{e} &= \log(e) \\ \text{EVF} &= \sum_{x'=1,\ldots,\overline{x}} [\beta V_{\tilde{e}}(x', 0, \mu')|G] \end{aligned}$$

Note that the value function is dependent upon on the entry rate ($V_{\tilde{e}}$). The mechanics are fairly straightforward. High expected discounted profit leads to a new, higher guess of entry, thereby driving expected discounted profit down. The inverse is, of course, also true. A fixed point occurs where $\log(\text{EVF}) - \log(f_e) = 0$ which implies (6) holds with equality. While the model's mechanics make it difficult to prove that Ψ is a contraction, numerical experiments confirm that it works for a variety of demand structures.