Outsourcing, Firm Innovation, and Industry Dynamics in the Production of Semiconductors

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PRELIMINARY

Abstract

I build a dynamic oligopoly model of firm innovation to isolate the equilibrium effects of outsourcing. Firms enter the industry each period and choose whether to produce in proprietary fabrication facilities or outsource production to lower marginal costs. Incumbent firms strategically invest to stochastically improve product quality and firm profits. I estimate the model using data from the semiconductor industry where outsourcing firms account for approximately one-third of revenue. The estimated model demonstrates that outsourcing increased entry (extensive margin) by relaxing the financial constraints for small firms but decreased research effort of incumbent, vertically-integrated firms (intensive margin). Global supply chains reduced marginal costs, increasing firm R&D and entry. Consumer welfare falls early in the transition path but outsourcing is ultimately beneficial for consumers indicating that effective government policy requires a long-run perspective.

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1 Introduction

Over the past forty years the world has become much more integrated as reductions in trade costs due to technological advancements (Hummels, 2007) and import tariffs due to international coordination (Bergstrand, Larch, and Yotov, 2015) increased bilateral trade significantly. An important feature of this increase in trade is that roughly two-thirds of international trade occurs in intermediate inputs (Johnson and Noguera, 2017) which indicates that global supply chains have become an integral part of the world economy. Much of this is driven by vertical specialization as different countries vie for segments of the global supply chain which align with their comparative advantage (Hummels, Ishii, and Yi, 2001). All of this serves to point out the quantitative importance of global supply chains and the importance of understanding the impact of sourcing decisions upon not only firm production costs but also the subsequent decisions lower marginal costs may enable (Antràs, Fort, and Tintelnot, 2017). The impact of sourcing on the evolution of industries, particularly the role of sourcing in influencing the equilibrium innovation decisions of firms and the subsequent evolution of the industries they inhabit, is not well understood, however.[1]

In this paper I study the impact of sourcing on firm innovation in the semiconductor industry – an industry which produces goods (e.g., microprocessors) which enable nearly every facet of modern life. The industry is highly-competitive and fast-paced as firms dedicate substantial resources towards creating new products. It has also changed substantially over the years as technological innovations increased the performance of its products and growing demand led to increases in industry revenue as well as the number of firms.[2] During the 1970s and 1980s, the industry was dominated by vertically-integrated device manufacturers (IDMs) which managed all components of the value chain (design, fabrication, testing, and distribution) in-house. Vertical integration provides these firms an opportunity to coordinate all facets of production and helps ensure the protection of intellectual property. These firms operate fabrication facilities around the world to take advantage of the comparative advantages (including tax benefits) offered by different countries.

While IDMs produce in-house (and potentially off-shore production elsewhere), an increasingly popular business model is to outsource all production to third-party, low-cost foundries overseas, largely Taiwan and China. Firms choosing this business model lack an internal fabrication facility and are known as "Fabless." Today, Fabless firms account for roughly one-third of all firms and one quarter of industry revenue. The Fabless business model proposes two advantages to the traditional IDM. First, outsourcing fabrication enables these firms to avoid the substantial capital investment required to build a fabrication facility. Second, outsourcing overseas enables these firms

[1] Igami (2018) shows that American firms in the hard disk drive industry survived increasing global competition by offshoring production to low-cost Asian countries but does not evaluate the impact on firm innovation decisions.

[2] This amounts to a financial corollary to Intel founder Gordon Moore's 1965 prediction, known as "Moore's Law", that the processing power of an integrated circuit doubles every year.In 1975 Moore amended his prediction to every two years – a prediction that fit the data amazingly well until 2012 when the pace of technological improvements began to slow.

to take advantage of lower input costs (e.g., wages, environmental regulations) in other countries as well as any scale effects as they pool production with other Fabless firms in third-party foundries. Thus, the Fabless business model is thought to decrease upfront costs as well as on-going production costs. Unfortunately, it also constrains the degree of specialization embedded in a product and exposes the firm to imitation risk. Thus, it appears that neither the IDM or Fabless business model is a dominant industry strategy but rather the two appear to likely coexist as they offer similar but differentiated products for consumers.

My objective is to evaluate the impact of outsourcing on the firm dynamics in this high-tech industry. To do so I develop a dynamic oligopoly model of innovation in which firms strategically outsource production overseas and invest to increase the quality of their product. To account for exogenous market growth I consider firm strategies which vary over time as the market grows and transitions between steady-states. The model serves two purposes. First, it demonstrates the value of outsourcing in this industry. Namely, the model predicts that outsourcing can enable entry of small firms by reducing the upfront costs of commercializing their product. Put differently, the model predicts that outsourcing may relax liquidity constraints facing firms much in the same way a government subsidy on capital expenditure lowers the cost of market entry. The model also predicts that when outsourcing reduces marginal costs of production, firm profits may increase leading to greater discounted future profits. The degree to which profits increase due to outsourcing, however, depends on the endogenous market power of the firms, or equivalently the degree to which reductions in cost are passed-through to consumers (Weyl and Fabinger, 2013). Put together, I use the model to demonstrate that outsourcing may encourage market entry by both lowering costs and increasing pay-offs and that these effects are particularly relevant for small firms who normally would not have been able to secure financing through other market mechanisms such as venture capital.[3] For an incumbent firm, the model predicts that, all else equal, an increase in discounted profits due to outsourcing increases the incentive to invest in quality-upgrading one's product.

As the model is also tractable, the second purpose is to test the quantitative significance of these predictions. I do so by estimating the model using data from the semiconductor industry, including detailed wafer pricing which enables me to identify the cost savings firms enjoy by outsourcing production abroad. The estimated model replicates moments in the data well and generates reasonable and statistically significant parameter values. I show that changes in the production costs associated with outsourcing have material effects on incumbent R&D (process innovation) as well as firm entry (product innovation). As the estimated entry and on-going R&D costs in the Fabless business model are less than for IDM firms, decreasing the benefits of outsourcing through either an increase in international trade costs or import tariffs leads to less outsourcing but more firm entry and on-going R&D. The ultimate effect is an increase in average product quality in the industry though consumer surplus falls due to higher prices as much of

[3] Venture capital firms are often the primary investors in the high-tech industry but they also require a return on investment of roughly 10x and have short investment horizons (5-7 years) so securing financing to cover the production of a new but not revolutionary chip design is practically infeasible.

the increase in production costs are passed onto consumers. Thus, outsourcing production abroad benefited consumers largely though lower production costs rather than improved firm innovation.

I show growth of outsourcing was largely due to the ability of firms to avoid the large cost of building a fabrication facility rather than lower production costs due to economies of scale from third-party facilities. I also find that the industry's evolution is sensitive to changes in the venture capital industry which would have impacted financing rates and therefore capital expenditure costs. These results indicate that outsourcing amounted to a new financial technology which decreased entry costs and enabled entry of smaller companies. Increased entry of Fabless firms ultimately led to increased competition for the traditional, vertically-integrated IDMs leading to less profits for these firms and ultimately less innovative effort. Consumer welfare along the transition path is negative early but becomes positive as the industry approaches the long-run steady-state. Thus, my results indicate that outsourcing improved the dynamic efficiency of the industry by enabling entry of new firms and that effective government policy requires a long-run perspective.

2 Related Literature

In this paper I empirically investigate the impact of outsourcing production overseas on the dynamics of an industry in which innovation is driven by both incumbent firms and new entrants. As such I contribute to two branches of economics: industrial organization and international trade.

The closest paper is that of Igami (2018) who uses a dynamic oligopoly model to explore the incentives of firms to offshore in the hard disk drive industry. This paper is, however, different in two important dimensions. First, my focus is on outsourcing rather than offshoring so my contribution is to show how globalization redefines the boundaries of the firm as well as its span of control (Lucas, 1978). Second, object of study is a growing industry where the the dynamics model allows for firm entry, on-going innovation, as well as outsourcing. This provides an opportunity to use the model to decompose the relative contributions of each channel towards explaining the relative roles each played.

As an empirical model of dynamic oligopoly, the paper aligns with the models of firm innovation such as Goettler and Gordon (2011), Ryan (2012), Collard-Wexler (2013), and Igami (2017, 2018). As in Goettler and Gordon (2011) and Igami (2017, 2018) my estimates are based on solving the static and dynamic parameters simultaneously – what has become known as the "full-solution approach." While this increases the computational burden, it also alleviates endogeneity concerns which may arise when employing a two-step estimation as in Bajari, Benkard, and Levin (2007).[4] To make the empirical exercise tractable, I restrict firm entry, pricing, and innovation strategies to be based on the expected firm size distribution rather than observed firm states as in a Markov Perfect Equilibrium. Instead, I employ the *Oblivious Equilibrium* concept introduced by

[4] See Berry and Compiani (2017).

Weintraub, Benkard, and Van Roy (2008) and extended to account for aggregate shocks (Weintraub, Benkard, and Van Roy, 2010).

In the semiconductor industry, early studies focused on the patenting motives[5] 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.[6]

This paper also contributes to a growing literature on the importance of international markets and global supply chains. Here, the closes the paper is Antràs, Fort, and Tintelnot (2017) who study the interaction of global sourcing on firm production costs and export decisions. My contribution therefore is to study extend the analysis of global supply chains to firm innovation decisions and industry dynamics.

The remaining paper is structured as follows. In Section 3 I introduces the model and equilibrium concept. In Section 4 I present information about the U.S. Semiconductor industry. Section 5 provides details on the estimation and presents the estimation results. In Section 6 I decompose the estimated model to quantify the relative importance of the various factors which contributed to outsourcing in this industry, while in Section 7 I evaluate the equilibrium effects of outsourcing on the evolution of the industry, including the implications for consumer welfare. I provide concluding remarks and discuss areas for further research in Section 8.

3 Model

Time is discrete and each period t is labeled $t = 1, 2, \ldots, \infty$. In each period t incumbent firms choose price to maximize static, one-period profits taking into account the distribution of competing firms as well as the demand of M_t heterogenous utility-maximizing consumers. After profits are realized, firms exit the industry at an exogenous rate. Surviving firms then invest to stochastically improve product quality where "quality" amounts to a latent demand-shifter where all-else-equal consumers prefer products of higher "quality." Each period potential entrants may choose to enter the industry and, if they do, they make a discrete choice whether to own and operate their own

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

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

fabrication facility or outsource production to a third-party. Once a firm chooses its business model (*i.e.*, whether to outsource) it cannot deviate from this choice in the future.[7]

3.1 Firms

I begin by discussing the strategic choices of firms where I assume that each firm produces a single product j of quality q. Firms produce their products via an in-house, proprietary fabrication facility or may outsource production to a low-cost third-party. Firms that produce in-house are denoted with a superscript "I" while outsourcing firms are denoted with a superscript "F." At the beginning of each period firms choose price in spot-markets and each consumer chooses the product which maximizes his or her utility. Some firms then exit at an exogenous rate while surviving firms invest in R&D to stochastically increase their product quality. I assume that firms make decisions upon their product quality and the expected industry state. This restricts the strategy space and makes solving the model computationally feasible by reducing the firm's optimization problem to be a single-dimensional dynamic programming problem. In the equilibrium firm beliefs about the expected state μ are correct.

Pricing. Labor is the only input into the production process and is supplied inelastically by households.[8] The marginal cost of production therefore is simply the wage rate where I set the marginal cost of type "I" firms equal to one and set the marginal cost of type "F" firms as λ_t where for values of λ_t less than one these firms have an advantage in production cost in period t.

I assume that each period there exists M_t utility-maximizing consumers. I make two simplifying assumptions which increase the model's empirical tractability significantly. First, consumers are myopic and maximize static utility. Second, firms have perfect foresight so the vector of consumers $\{M_t\}_{t=1}^{\infty}$ is both exogenous and known to firms when they make decisions.

As consumer demand is static and production costs are fixed (*i.e.*, I ignore the possibility of learning-by-doing effects), equilibrium prices are found as the solution to a static period t non-cooperative Bertrand-Nash game among the competing firms. I define as the expected industry state μ as the measure of product qualities in the industry where $\mu(q, I)$ is the mass of type "I" firms with product quality q while $\mu(q, F)$ corresponds to the mass of type "F" firms with product quality q. The firm of type m={I,F} which produces product j in period t therefore chooses price p_{jt}^{m} to maximize static profits taking into account the product qualities ($q_{\cdot t}$), market shares $s_j^{\mathrm{m}}(q, p; \mu)$, and prices of the competition ($p_{\cdot t}$) satisfying the following first-order condition:

[7] While this assumption does make solving the model easier, the motivation is that in the empirical exercise with data form the semiconductor industry there are few instanced where firms switch business models.

[8] For capital-intensive industries (as in the empirical application considered here), one should view the labor input as "effective" labor units which combine both capital and manual labor.

$$
\begin{aligned}
p_t^{\mathrm{I}}(q;\mu_t,M_t) &= 1+\underbrace{\left[\frac{\partial s_t^{\mathrm{I}}(q,p;\mu_t,M_t)}{\partial p_t^{\mathrm{I}}}\right]^{-1}\times s_t^{\mathrm{I}}(q,p;\mu_t,M_t)}_{b_t^{\mathrm{I}}(q,p;\mu_t,M_t)} \\
p_t^{\mathrm{F}}(q;\mu_t,M_t) &= \lambda_t+\underbrace{\left[\frac{\partial s_t^{\mathrm{F}}(q,p;\mu_t,M_t)}{\partial p_t^{\mathrm{F}}}\right]^{-1}\times s_t^{\mathrm{F}}(q,p;\mu_t,M_t)}_{b_t^{\mathrm{F}}(q,p;\mu_t,M_t)}
\end{aligned}
\tag{1}
$$

where period t subscripts indicate that equilibrium prices can vary across time due to changes in type "F" firm marginal cost (λ_t), variation in market size (M_t), and changes in the firm size distribution (μ_t). The terms $b_{jt}^{\mathrm{m}}(q,p;\mu)$ are per-unit equilibrium markups which depend upon the firm's product quality and the price it chooses plus the prices chosen by its competition, including both type "F" and "I" firms. Thus, markups are not assigned exogenously but are rather derived endogenously via the firms' optimal pricing decisions.

Note also that consumer demand $s^{\mathrm{m}}(q,p,\mu)$ is not a function of the identity of product j but rather solely on its quality (q), the product qualities of competing varieties μ, and upon the prices chosen by the firms (p). This is a common approach to modeling consumer demand which dates back to Lancaster (1966). I restrict attention in the pricing game to pure strategy equilibria and given that these single product firms face a constant marginal cost, there exists a unique Nash equilibrium in pure strategies denoted $p^{\mathrm{m}\star}(q,\mu)$ $\forall \mathrm{m}\in\{\mathrm{F},\mathrm{I}\}$ which solves the system of equations defined by (1) (Caplin and Nalebuff, 1991). Moreover, two firms of the same product quality and business model will optimally choose the same prices while two firms of the same product quality but different business model will choose different prices because of differences in marginal cost due to $\lambda\neq 1$ and differences in consumer demand captured through $s^{\mathrm{m}}(q,p;\mu)$.

Equilibrium profit for a firm which produces a product of quality q in industry state μ is then

$$
\begin{aligned}
\pi_t^{\mathrm{I}\star}(q;\mu_t,M_t) &= \left[p_t^{\mathrm{I}\star}(q;\mu_t)-1\right]\times s_t^{\mathrm{I}\star}\big(q,p_t^{\star};\mu_t,M_t\big)\times M_t, \\
\pi_t^{\mathrm{F}\star}(q;\mu_t,M_t) &= \left[p_t^{\mathrm{F}\star}(q;\mu_t)-\lambda_t\right]\times s_t^{\mathrm{F}\star}\big(q,p_t^{\star};\mu_t,M_t\big)\times M_t.
\end{aligned}
\tag{2}
$$

Research. Firm quality evolves over time depending on a firm's investment in quality-upgrading its variety and idiosyncratic productivity shocks. I model the evolution of product quality as follows: After profits are realized, incumbent firms exit the industry at an exogenous rate δ_t or, put differently, have and a $1-\delta_t$ probability of surviving to produce the following period. Note that δ_t is common to all firms but may vary across time. A surviving type m firm invests $c_t^m(k)$ in period t and has a probability k of having quality $q+\Delta_q$ and probability $1-k$ of having quality $q-\Delta_q$ in the following period $t+1$. I assume that the research cost $c_t^m(k)$ is increasing k so increasing the probability of R&D success is expensive.

This R&D process exhibits some important qualities. First, it is increasing in both q and k so a firm which produces a high quality product today is likely to produce a high quality product tomorrow – as is a firm which increases its R&D investment (*i.e.*, $c_t^m(k)\uparrow$) also increases its chances of developing a high quality product tomorrow (since $c_t^m(k)$ is increasing in k). Second, I allow for differential research abilities between the two firm types. Lastly, I assume that the research effort of other firms has no effect on research costs of an individual firm so there exists no explicit crowding out of investment or technological spillovers.

An individual firm of type m $\in \{\mathrm{F},\mathrm{I}\}$ which produces a product of quality q and faces industry state μ_t solves the following recursive problem:

$$\begin{aligned} V_t^m(q,\mu_t,M_t) &= \overbrace{\pi_t^m(q,\mu_t,M_t)}^{\text{Static Profit}} + \\ & (1-\delta_t^m)\times \max_{k\in[0,1]} \left\{ \begin{array}{c} \underbrace{-c_t^m(k)}_{\text{R\&D Cost}} + \\ \\ k\beta \underbrace{V_{t+1}^m(q+\Delta_q,\mu_{t+1},M_{t+1})}_{\text{Quality Improves}} + \\ \\ (1-k)\beta \underbrace{V_{t+1}^m(q-\Delta_q,\mu_{t+1},M_{t+1})}_{\text{Quality Decreases}} \end{array} \right\} \\ \text{s.t.} \quad \mu_{t+1} &= \Upsilon(\mu_t,M_t;k_q,k_{-q}),\ \underbrace{M_{t+1}=\Psi(M_t)}_{\text{Perfect Foresight}}. \end{aligned} \tag{3}$$

where again the inclusion of period subscripts communicates the fact that I allow for variation in period t profits due to changes in demand via M_t. Also note that the firms' value function and corresponding investment decision rules are non-stationary.[9] Define $k_t(q,\mu_t)$ as the period t decision rule for a firm with product quality q in industry state μ_t and k_{-t} as the investment decision for the other firms in the industry. Thus, the industry state μ evolves according to $\Upsilon:\mu_t\rightarrow\mu_{t+1}$. From (3) we observe that spillovers do not impact research costs but that the research effort of other firms may however impact equilibrium research effort of an individual firm through the evolution of the aggregate industry state and the subsequent impact to expected profits: $E[V_{t+1}(\cdot,\mu_{t+1})]$.

Entry. Market entry is similar to that of Seim (2006). There exists a large set of prospective firms $\mathcal{N}$ which may enter each period. A period t prospective entrant has thee choices. It can choose to enter the industry to become a type "I" firm, it can choose to enter the industry to become a type "F" firm, or it can choose to not enter the industry. Entering either as a type "I" or type "F"firm requires a one-time entry cost of $f_e^{\mathrm{I}}+\varepsilon^{\mathrm{I}}$ and $f_e^{\mathrm{F}}+\varepsilon^{\mathrm{F}}$ where $(f_e^{\mathrm{I}},f_e^{\mathrm{F}})$ are common to all firms but $(\varepsilon^{\mathrm{I}},\varepsilon^{\mathrm{F}})$ are random idiosyncratic draws from an extreme value distribution.[10] Upon paying the

[9] While this complexity is not fundamentally necessary to address the research questions posed in this paper, it is an important feature in the empirical exercise for which I use the model.

[10] In contrast Seim (2006) assumes that firms have idiosyncratic product qualities which are distributed i.i.d. extreme value.

entry cost each firm receives an initial quality from the time-invariant product quality distribution G which is common to firms of both business types. Define $\tilde{V}_t^f(\mu)$ as the expected discounted value of entry as a type $f \in \{\mathrm{F}, \mathrm{I}\}$ firm where

$$\begin{aligned} \tilde{V}_t^{\mathrm{I}}(\mu_t) &= \beta \textstyle\sum_{x \in \mathcal{Q}} V_t^{\mathrm{I}}(x, \mu_{t+1}) dG(x) \\ \tilde{V}_t^{\mathrm{F}}(\mu_t) &= \beta \textstyle\sum_{x \in \mathcal{Q}} V_t^{\mathrm{F}}(x, \mu_{t+1}) dG(x) \\ \text{s.t. } \mu_{t+1} &= \Upsilon(\mu_t; k_t, k_{-t}) \,. \end{aligned} \tag{4}$$

In expectation each entrant earns nonnegative profits so the probability a prospective entrant chooses to be a type "I" firm is

$$\mathrm{Pr}_t^{\mathrm{I}}(\text{entry}) = \frac{exp(\tilde{V}_t^{\mathrm{I}} - f_{e,t}^{\mathrm{I}})}{1 + exp(\tilde{V}_t^{\mathrm{I}} - f_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}} - f_{e,t}^{\mathrm{F}})}$$

while the probability a prospective entrant chooses to become a type "F" firm is

$$\mathrm{Pr}_t^{\mathrm{F}}(\text{entry}) = \frac{exp(\tilde{V}_t^{\mathrm{F}} - f_{e,t}^{\mathrm{F}})}{1 + exp(\tilde{V}_t^{\mathrm{I}} - f_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}} - f_{e,t}^{\mathrm{F}})} \,.$$

The number of entrants of each firm type is $\{\mathcal{E}^{\mathrm{I}}, \mathcal{E}^{\mathrm{F}}\}$ is simply

$$\begin{aligned} \mathcal{E}_t^{\mathrm{F}} &= \mathrm{Pr}_t^{\mathrm{I}}(\text{entry}) \times \mathcal{N} \\ \mathcal{E}_t^{\mathrm{F}} &= \mathrm{Pr}_t^{\mathrm{F}}(\text{entry}) \times \mathcal{N}, \end{aligned} \tag{5}$$

where market entry will vary over time due to variation in the expected discounted profits of entry (Equations 4).

We are now in a position to characterize the law of motion for the industry state defined thus far as $\Upsilon : \mu_t \to \mu_{t+1}$. Specifically, for all firm types m $\in \{\mathrm{I}, \mathrm{F}\}$ the industry state evolves according to the following law of motion:

$$\begin{aligned} \mu_{t+1}^m(q) &= (1 - \delta_t^m) \cdot \Big[\underbrace{k_t^m(q - \Delta_q, \mu_t) \times \mu_t^m(q - \Delta_q)}_{\text{Firms successfully improve quality}} \Big] + \\ & (1 - \delta_t^m) \cdot \Big[\underbrace{\Big(1 - k_t^m(q + \Delta_q, \mu_t)\Big) \times \mu_t^m(q + \Delta_q)}_{\text{Firms unsuccessful at improving quality}} \Big] + \underbrace{\mathcal{E}_t^m dG(q)}_{\text{Entry}} \,. \end{aligned} \tag{6}$$

3.2 Consumer Demand

Consumer demand follows the large literature of discrete choice in the Industrial Organization literature. In each period t a consumer i of M_t chooses the optimal product among the set of differentiated products offered by the firms. A consumer therefore purchases the good which offers her the highest level of utility taking into account differences in both prices and product "quality" q among the products. There is no storage so the consumer's optimization problem is static.[11]

Mathematically, consumer i derives an indirect utility from buying good j at time t that depends on price and product j's quality $q_j \in \mathcal{Q}$:

$$\begin{aligned} u_{ijt} &= q_j + \alpha p_{jt} + \omega p_{jt} q_j + \mathbb{1}_{\{j \in \mathrm{I}\}} \xi^{\mathrm{I}} + \epsilon_{ijt} \,, \\ &\text{where} \;\; i = 1, \ldots, M_t; \quad j = 1, \ldots, J_t \,, \end{aligned} \tag{7}$$

where ξ^{I} is a demand shifter for type I firms, $\alpha \in \mathbb{R}^1$ accounts for the marginal utility of money, and J_t is the set of products available to the consumer. Note that product "quality"amounts to a demand shifter and α attenuates the degree to which consumers value quality versus price where higher priced goods while ω allows for the price sensitivity to vary with product quality. For simplicity I assume that $(\alpha, \omega, \xi^{\mathrm{I}})$ are time-invariant. Consumers have heterogenous tastes which I define as ϵ_{ijt} and I assume these differences are random and follow an i.i.d. type I extreme value distribution. For simplicity I assume there is no outside option so each consumer chooses to purchase one of the products offered. Conditional on the set of product qualities and prices, the set of consumers which purchase product j depends on consumer differences in these heterogenous tastes for quality:

$$A_{jt}\left(q_{\cdot}, p_{\cdot t}, ; \alpha, \omega, \xi^{\mathrm{I}}\right) = \{\epsilon_{ijt} | u_{ijt} \geq u_{ikt} \quad \forall k = 0, 1, \ldots, J_t\} \,, \tag{8}$$

My assumption that these differences are random and distributed extreme value is useful as it enables the researcher to integrate over the distribution of ϵ_{it} to obtain the probability of observing A_{jt} analytically. I define s_{jt} as the probability that consumer i purchases product j in period t:

$$\begin{aligned} s_{jt} &= \frac{exp(q_j + \alpha p_{jt} + \omega p_{jt} q_j + \mathbb{1}_{\{j \in \mathrm{I}\}} \xi^{\mathrm{I}})}{\sum_{f \in J_t} exp(q_f + \alpha p_{ft} + \omega q_f p_{ft} + \mathbb{1}_{\{f \in \mathrm{I}\}} \xi^{\mathrm{I}})} \\ \Rightarrow \; s_t^{\mathrm{m}}(q; \mu) &= \frac{exp\left(q + \alpha p_t^m(q; \mu_t) + \omega p_t^m(q; \mu_t) q + \mathbb{1}_{\{m = \mathrm{I}\}} \xi^{\mathrm{I}}\right)}{\sum_{k \in \{\mathrm{I}, \mathrm{F}\}} \sum_{x \in \mathcal{Q}} \mu_t^k(x) \times exp\left(x + \alpha p_t^k(x; \mu_t) + \omega p_t^k(x; \mu_t) x + \mathbb{1}_{\{k \in \mathrm{I}\}} \xi^{\mathrm{I}}\right)} \,. \end{aligned} \tag{9}$$

As consumers are ex ante identical, $s_t^{\mathrm{m}}(q; \mu_t)$ is also the predicted market share for a period t firm with quality q which faces competition μ_t. The firm's demand is therefore $y_t^{\mathrm{m}}(q; \mu_t, M_t) =$

[11] In contrast, Goettler and Gordon (2011) model the consumer's choice problem as dynamic where consumers optimally wait to upgrade their technology.

$s_t^{\mathrm{m}}(q;\mu_t) \times M_t$. All else equal, a firm's demand is increasing in its product quality and the number of consumers in the market but decreasing price (provided $\alpha < 0$) and the number of competitors in the market.

3.3 Equilibrium

An important feature of the model is that I assume firms make their entry, outsourcing, pricing, and innovation decisions strategically taking into account the expected (but not necessarily observed) industry state. Thus, I solve this dynamic model of firm behavior by extending the "Oblivious Equilibrium" (hereafter "OE") concept developed by Weintraub, Benkard, and Van Roy (2008) to account for non-stationary firm behavior.[12] A "Non-stationary Oblivious Equilibrium" (hereafter "NOE") is a set firm entry strategies $\{\mathcal{E}_t^{\mathrm{I}}(\mu_t), \mathcal{E}_t^{\mathrm{F}}(\mu_t)\}$ satisfying (5), a set of pricing conditions $\{p_t^{\mathrm{I}}(\mu_t), p_t^{\mathrm{F}}(\mu_t)\}$ which maximize spot-market profits (1), and firm investment $\{k_t^{\mathrm{I}}(\mu_t), k_t^{\mathrm{I}}(\mu_t)\}$ such that the law of motion for the expected industry state μ_t follows (6) for all periods t. It is important to note that a NOE nests the OE of Weintraub, Benkard, and Van Roy (2008).

4 The Semiconductor Industry

In this section I discuss details of the semiconductor industry and pay particular attention areas which map to model. Semiconductor firms are those firms engaged in the design and/or fabrication of semiconductors – any material whose electrical conductivity has values between that of a conductor and a insulator. Integrated circuits (ICs) comprise the bulk of industry revenue[13] and are generally considered any network of transistors fabricated on a surface to process binary data by switching on and off.

The semiconductor industry 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.[14] While the industry provides products for a wide-variety of hi-tech sectors, personal computers still account for the majority of industry sales.

There are four kinds of products in the industry; three of which I include in the analysis (Table I). Firms such as Intel and Advanced Micro Devices (AMD) produce microprocessors which amount to integrated circuits containing one or more central processing units (CPUs). Example products include personal computers, tablets, and servers. The 32- and 64-bit microprocessors

[12] Weintraub, Benkard, and Van Roy (2008) show that for markets with a large number of competing, firms can make near-optimal decisions based solely on the expected industry state rather than on the observed industry state. Thus, the *Oblivious Equilibrium* concept they develop can be seen as an approximation for the Markov Perfect Nash Equilibrium concept commonly used in the literature.

[13] ICs accounted for 85% of total industry revenue in 2004 - World Semiconductor Trade Statistics, "WSTS Semiconductor Market Forecast, Autumn 2004," Press Release, November 2, 2004. (www.wsts.org).

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

in PCs and servers are based on x86, POWER, and SPARC chip architectures while tablets are usually based on an ARM chip architecture. Less powerful microprocessors (e.g., 8, 16, and 24-bit) are often employed in toys and vehicles.

Table I: Semiconductor Firms and Products

Semiconductor Products	Example Firms	Example End-Products
1. Microprocessors	AMD, Intel, ...	Computers, servers
2. "System on a Chip"	Broadcom, Nvidia, Qualcomm, ...	Mobile phones
3. Commodity integrated circuits	Analog Devices, Xilinx, ...	Bar code scanners
4. Memory	IBM, Samsung, Toshiba, ...	Computers, flash drives

The second category "system on a chip" (or SoC) is the newest kind of semiconductor chip as it combines all the necessary components for an entire system on a single chip. These products are popular among small devices such as smartphones as they integrate CPUs with graphics, camera, as well as audio and video processing. Primary firms in this market include Nvidia, Broadcom, Qualcomm.[15] The third category included in the analysis is commodity integrated circuits commonly used in simple technological devices such as bar code scanners. The final category commonly commonly considered as part of the industry is the area of memory chips, particularly flash memory which are produced by large technological conglomerates such as IBM and Samsung. As these companies create a large array of products outside the industry, identifying the importance of outsourcing towards the evolution of this product group was difficult and I therefore excluded them from the analysis.

There are four primary components of the value chain: design, fabrication, testing, and sales/ distribution. During the design stage, skilled design engineers construct prototypes of next-generation chips using high-end, expensive electronic design automation (EDA) software. Upon completion, these plans are delivered to a potentially external fabrication facility where the chip circuits are constructed in successive layers on the surface of a flat silicon wafers. Firms which conduct this stage internally must incur a large fixed capital investment (≈$2 billion) to build a plant (a "fab") consisting of a wide variety of expensive equipment capable of building the chips under extreme environmental requirements for cleanliness. During the Assembly stage, the wafers are split into individual chips (a "die") for distribution to customers.

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. In a 1965 paper, Intel co-founder Gordon E. Moore noted that the capabilities of the integrated circuit doubled roughly every 18 months.[16] This prediction became known as "Moore's

[15] To further indicate the importance of this industry: In early 2018 Singapore-based Broadcom attempted a hostile takeover of Qualcomm ($120 billion) which was later invalidated for national security reasons by the Trump administration. Intel has since expressed interest in acquiring Qualcomm to solidify its position to deliver 5g mobile services in the future.

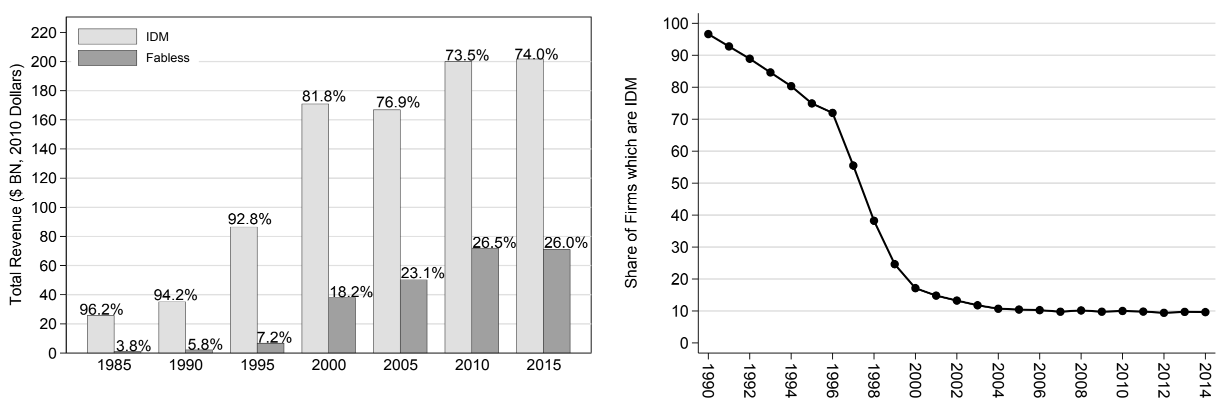
[16] At the time, he was referring to the number of transistors a firm could inexpensively place on a single silicon wafer. Today, advancement generally refers more generically to processor speed.

Law" and 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 has increases from 11% of firm sales in the early 1980s to 31% of firm sales for the period 2000-2005.

4.1 A Changing Marketplace

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 Figure 1 I document that the industry has undergone a significant transformation. In panel (a) I document that total industry sales have grown substantially since the early 1990s, driven primarily though increasing expenditures on personal and commercial information technology. Concurrent with this growth was a shift in business model from vertically integrated device manufacturers (IDMs) towards niche design firms which outsource manufacturing to low cost fabrication plants. Since this latter group lacks any kind of production/ fabrication abilities, they became known as as "fabless." Today, roughly one-quarter of all industry revenue is generated by fabless firms. In panel (b) I document that a dramatic shift in the number of firms operating in the industry where in 1990 nearly every firm was vertically-integrated while today only about 10% of firms operate their own fabrication facility.

Figure 1: A Growing and Changing Market



(a) Revenue Share (b) Composition of Firms

Notes: In panel (a) I document industry revenue growth (also see Figure 11) and the increasing revenue share of fabless firms. In panel (b) I document the changing composition of firms. Source: Compustat and Global Semiconductor Alliance.

Growth of the fabless business model (*i.e.*, of outsourcing) is predicated on the ability of firms to produce quality goods at efficient scale. Outsourcing fabrication is particularly attractive in this industry as semiconductors tend to be high value but weigh little thereby incurring little transportation cost. As many low-wage countries lack the technical expertise and capital infrastructure to establish viable foundries, most foundries are located in a small set of countries including China, Europe, Japan, Taiwan, and the United States (Table VI). While the vast majority of outsourcing is done overseas (where Taiwan accounts for approximately 59% of all outsourced wafers produced), the United States foundries account for four percent of all third-party wafers produced. This indicates that global supply chains have played an important though not necessarily pivotal role in facilitating growth of the fabless business model.

Table II: Fabless Production Market Share by Country

Year	China	Japan	Korea	Singapore	Taiwan	USA	Other
2004	11.07	6.07	5.78	14.56	45.42	3.75	13.35
2005	2.47	4.89	2.47	6.04	69.06	2.66	12.41
2006	2.36	7.37	5.58	13.35	57.26	3.54	10.54
2007	6.38	2.95	3.18	18.74	57.81	2.19	8.75
2008	6.44	6.42	4.69	14.97	57.90	2.00	7.58
2009	6.87	6.82	2.22	9.49	64.83	4.30	5.47
2010	7.42	11.73	3.42	6.90	58.75	7.16	4.62
2011	13.84	8.02	4.44	4.05	59.07	6.48	4.10
2012	4.99	4.01	7.43	3.19	68.53	4.45	7.40
2013	5.97	14.45	5.70	2.83	62.91	3.74	4.40
2014	9.30	24.09	5.97	5.26	46.31	4.14	4.93
Total	7.17	8.38	4.71	8.70	59.38	4.13	7.53

Notes: Author's calculation based on GSA wafer pricing survey (2004-2015). Statistics reflect the share of wafers produced by third-party fabrication facilities in a given year. "Other" includes Europe and other countries with small market shares (e.g., India, Israel).

The majority of third-party foundries which produce Fabless products are located in Southeast Asia (Table II). The common story for this concentration is that these countries have a sufficiently skilled workforce to enable the complex production of semiconductor wafers while low wages and relatively weak regulations (e.g., environmental standards) enable low-cost production without sacrificing much in terms of quality. I quantify the reductions in production cost from outsourcing using data on semiconductor wafer fabrication prices attained from a proprietary database collected by the Global Semiconductor Alliance (GSA). The GSA is a nonprofit industry organization consisting of fabless firms. Each quarter the organization surveys its members to collect information on prices, quantities, and characteristics of their orders from both domestic and foreign foundries. Responses are anonymous and firms which participate are granted access to the results. The dataset consists of 14,692 individual quarterly responses to the "Wafer Fabrication & Back-End Pricing Survey" covering years 2004-2015. According to GSA the sample is representative of the industry and accounts for roughly one-fifth of all fabless semiconductor wafers produced worldwide.

The data include nominal price paid, the number of wafers purchased, and the foundry's country location. I also observe characteristics about the wafer, including the line width, wafer size, and number of layers. I can therefore examine how foundry wafer prices vary by foundry location after controlling for physical characteristics. U.S. foundaries produced on average 3.96% of the wafers during the sample. In comparison, fabrication plants in Taiwan, Singapore, and China accounted for 58.22%, 9.06%, and 7.42% of the market, respectively. I cannot identify the specific foundry which fulfilled each order though the dominance of Taiwan Semiconductor Manufacturing Corportation (TSMC) in the Taiwanese market, Semiconductor Manufacturing International Corporation (SMIC) in Chinese market, and Chartered Semiconductor in Singapore market suggests that transactions which involve wafers fabricated in the Taiwan, Chinese, and Singapore markets where fulfilled by these firms. Thus, while there are a variety of foundries producing semiconductor wafers for fabless semiconductor firms, the bulk of the wafers are produced overseas in Taiwan, presumably by TSMC.[17]

The data therefore enable me to evaluate differences in production cost (proxied by foundry price) across countries. I can therefore estimate the price of fulfilling an order with a US-based foundry versus a foundry based in Asia. If one is willing to assume that the US foundry price is a good approximation for the marginal cost of producing in-house, the estimated differences in foundry prices also pins down the cost benefits underlying outsourcing.

Table III: Cost Advantages of Outsourcing

dep: log(Price)	(1)	(2)	(3)	(4)
China/ Taiwan				-0.2695***
				(0.0328)
China	-0.2845***	-0.5108***	-0.5152***	
	(0.0397)	(0.0304)	(0.0310)	
Taiwan	0.2752***	-0.2366***	-0.2469***	
	(0.0285)	(0.0339)	(0.0342)	
Malaysia	-0.4033***	-0.5883***		
	(0.0775)	(0.0629)		
Singapore	-0.1096**	-0.3320***		
	(0.0347)	(0.0358)		
Metal Layers		0.1142***	0.1200***	0.1279***
		(0.0060)	(0.0060)	(0.0061)
Process Masks		0.0114***	0.0117***	0.0120***
		(0.0011)	(0.0011)	(0.0011)
Poly Layers		0.0306**	0.0206	0.0069
		(0.0108)	(0.0115)	(0.0119)
lnQ		-0.0464***	-0.0471***	-0.0513***
		(0.0027)	(0.0029)	(0.0029)
Constant	6.9291***	6.7414***	6.7403***	6.7345***
	(0.0274)	(0.0518)	(0.0510)	(0.0519)
Time FEs	X	X	X	X
Product FEs		X	X	X
R^2	0.0743	0.8022	0.8003	0.7930
N	10,685	10,685	9,468	9,468

Notes: Table presents projections of log wafer price onto foundry location controlling for locations. Reference category is foundries located in the United States. Robust standard errors reported in between parentheses with p-values denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In Table III I present a series of hedonic price regressions to uncover why TSMC has such dominant market share. In column (1) I project log price onto foundry location using foundries located in the United States as the reference category and only controlling for differences in price over time via year fixed effects. This regression explains little about the variation in price (low R^2) and suggests TSMC actually charges a higher price relative to U.S. foundries. In the remaining

[17] Unfortunately, there is no information regarding buyers.

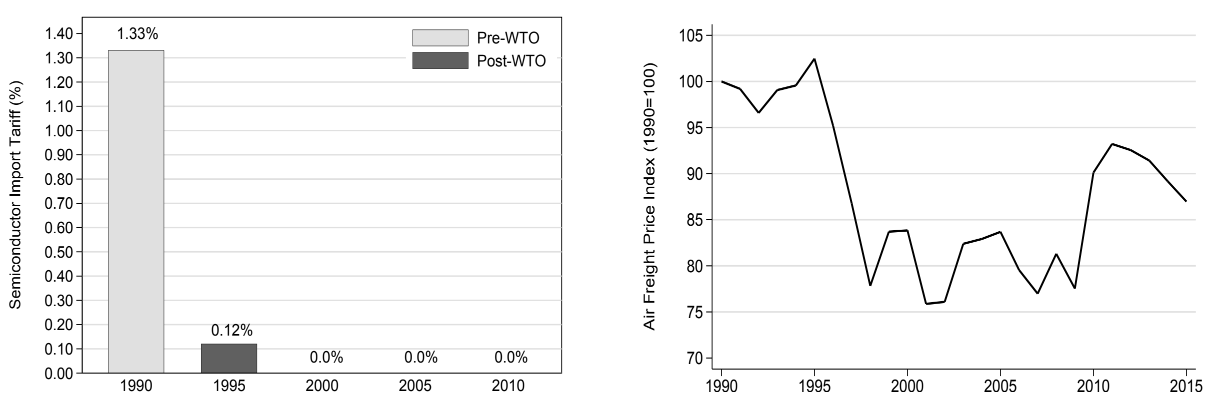
columns I include covariates for product characteristics as well as product-level fixed effects which I define as the process size and wafer size pair.

Including product characteristics increases the models' overall fit dramatically. We also observe intuitive coefficients on product characteristics where increasing the number of metal layers, process masks, or poly layers increases the complexity of the production process leading to a higher price. The industry also appears to offer quantity-discounts as larger orders lead to lower prices.

Adding product characteristic information has no qualitative effects on the estimated differences in price across foundries located in different countries. We still observe substantial price variation by location where wafers produced in China overseas are half as expensive to produce as in the United States while contracting with TSMC amounts to a 24% reduction in price. When I restrict attention to just variation between fabless contracts in the United States, China, and Taiwan (*i.e.*, the majority of the observations) we observe that contracting with a foundry in the either China or Taiwan is 26.95% less expensive than contracting with a foundry in the United States – a significant cost advantage.

The fact that foreign countries can produce products less expensively is a necessary but not sufficient condition for outsourcing and there are additional factors which facilitated growth of the Fabless business model. First, doing business overseas can be expensive since doing so requires shipping finished product back to the United States and paying any relevant import duties. An additional motivating factor therefore is the fact that international trade costs have fallen significantly since the 1970s. Some of this is due to multilateral trade agreements which have driven import tariffs to historic lows (Bergstrand, Larch, and Yotov, 2015) while some is do to reductions in transportation cost (Hummels, 2007).

Figure 2: Reductions in Trade Costs



(a) Import Tariff (b) Inbound U.S. Air Freight Prices

Notes: Panel (a) is the official import tariff applied to semiconductor devices (e.g., wafers). Source: United Nations Trade Analysis Information System (TRAINS). Panel (b) presents the real inbound air freight price index as calculated by the U.S. Bureau of Labor Statistics and deflated using U.S. consumer price index. Benchmark year is 1990.

In Figure 2 I show that the semiconductor industry benefited from both of these effects. In panel (a) we see that import tariffs for semiconductors fell to zero after the implementation of the Uruguay Trade round – the same trade round which created the World Trade Organization. In panel (b) we see that the cost of air freight, the primary transportation medium of semiconductors, also fell during the period in which we observe an increase in outsourcing. Hummels (2007) documents that transport costs for products traveling inbound to the United States during the 1990s amounted to $8 - 13\%$ of total product value – a significant amount.

Table IV: IDM and Fabless Firm Performance Over Time

	1980-1989		1990-2009		2010-2014	
Variable	IDM	Fabless	IDM	Fabless	IDM	Fabless
Gross Margin	43.18	45.42	44.26	54.81	41.94	57.76
R&D Expense / Revenue	11.63	14.25	16.28	24.57	16.18	25.12
Revenue Increases	61.58	75.22	66.83	67.48	63.10	64.64
Rank Increases	57.62	67.22	58.98	62.23	41.34	37.84
Capital Expense / Revenue	13.23	9.93	12.45	10.07	11.70	7.76
Exit Rate	3.73	0.00	4.32	3.98	9.42	10.52

Notes: Author's calculations based on Standard & Poor's Compustat (1980-2014). All statistics in percent. Variables described in the text. All variables reflect averages for the corresponding sample.

In Table IV I compare the financial performance of IDM and Fabless firms during the sample and I document two stylized facts. First, while both IDM and Fabless firms possess market power, outsourcing production enables Fabless to command higher margins. Second, incumbent firm R&D plays an important role in the industry regardless of business model.

In terms of static profitability I focus on gross margins defined as firm revenue minus "cost of goods sold" divided by revenue. Both IDM and Fabless firms have market power across the sample and Fabless firms, on average, have higher margins. Firms in this market also invest significant resources in research and development: As a percent of sales, IDM and Fabless firms invest between 11.6% and 25.12% in research and development, respectively. To put these numbers in perspective, the average R&D expense rate in Manufacturing (SIC 2000-3999), Computers and Electronic Equipment (SIC 357X, 3861), and Pharmaceuticals (SIC 283X) sectors were 10.7%, 16.0% and 55.3% during the sample, respectively.

Of course merely investing in research and development does not guarantee a successful innovation. I define successful R&D as a research expense which increases the firm's period $t + 1$ revenue ($R_{j,t+1}$) relative to its period t revenue ($R_{j,t}$). Using this metric we observe that between 60% and 70% of IDM and Fabless firms successfully increase their year-over-year revenue during the sample and their exists little difference between the business models, particularly outside the earliest part of the sample. To isolate improvements in revenue relative to the competition from increases in overall market revenue (Figure1, Panel a), in row "Rank Increases" I evaluate the percent of firms who successfully increase their competitive position. Define average period t revenue as $\overline{R}_t$. I say firm j's research is successful if its revenue relative to the competition increases from across periods, *i.e.*, $\frac{R_{j,t}}{\overline{R}_t} < \frac{R_{j,t+1}}{\overline{R}_{t+1}}$. Research efforts of both firm types are generally successful and there little exists variation across the sample. R&D success is tempered, however, by firm exit rates which vary across the sample.[18] Thus, the typical entrepreneur commercializes her idea in either a IDM or Fabless firm and each period chooses to spend significant resources in research & development to increases the firm's competitive positioning and revenue. At some point, however, she chooses to exit the industry.

5 Estimation

The objective of this research paper is to assess the implications of outsourcing on firm innovation decisions and I use the semiconductor industry – an important, research-intensive industry – as a case study. Since firm innovation is an endogenous choice among firms, I use the model presented in Section 3 as a laboratory to investigate how changes in model primitives such as the cost advantage from outsourcing impacts firm innovation decisions. In this section I describe how I estimate key model parameters, discuss identification, and present estimation results.

5.1 Preliminaries

Time periods are defined in years where $t = 1990, ..., 2014$. I assume that all new entrants regardless of business model draw their initial quality level from a time-invariant Pareto distribution with shape parameter equal to one (also known as the Zipf distribution). I choose stochastic exit rates which vary across time and business model using observed Semiconductor firm exit rates in Compustat. I chose the interval between the product quality ladders, Δ_q, such that the standard deviation of the growth rate of employment for large firms is 25% per year – a value consistent with Atkeson and Burstein (2010) and Davis, Haltiwanger, Jarmin, and Miranda (2007). It is important to note that product qualities q are latent variables observed only through differences in firm revenue so the quality ladder firms use to differentiate themselves is important not in levels but rather in differences between quality rungs and the relative position of the competition.

For ease of exposition I only required the R&D cost function in Section 3 to be increasing in the innovation success probability k but of course estimating the model requires placing structure on this functional form. I do so by assuming $c^{\mathrm{I}}(k)_t = w^r_t \times exp(k)$, $c^{\mathrm{F}}(k)_t = \rho w^r_t \times exp(k)$ where w^r_t is the research cost which I allow to vary across time. Allowing this cost function to vary by firm type (via ρ) provides an opportunity for R&D effort in process innovation to differ across business models just as differences in entry costs $\{f^{\mathrm{I}}_e, f^{\mathrm{F}}_e\}$ allows for systematic differences in firm entry across different business models. Thus, the estimated model allows for exogenous shocks to alter not only the number and composition (IDM vs Fabless) of firms in the industry but also allows for different levels of equilibrium R&D across firm types.

[18] I define firm exit if a firm disappears from the data set due to either bankruptcy (liquidation) or acquisition.

5.2 A Simulated Minimum Distance Estimator

Estimating the model requires identification of the remaining parameters which I define as $\theta = \{\alpha, \omega, \xi^{\mathrm{I}}, \rho, \lambda_t, w_t^r, M_t, f_{e,t}^{\mathrm{I}}, f_{e,t}^{\mathrm{F}}\}$. I estimate these parameters via the Simulated Minimum Distance estimator proposed by Hall and Rust (2003) and used in Goettler and Gordon (2011). The estimator amounts to a special case of the indirect inference estimator (e.g., Gourieroux, Monfort, and Renault 1993) as well as the generalized method of moments estimator of Hansen (1982) later modified to include simulation by Pakes and Pollard (1989). The underlying idea is to choose parameters which generate equilibrium moments consistent with the data. Put differently, the estimator minimizes the distance between key moments in the data and their simulated counterparts in the model. It therefore resembles calibration techniques common in the macroeconomics literature. A key difference from calibration, however, is that under reasonable assumption regarding identification and asymptotic stationarity, one can calculate standard errors for the estimated parameters.

Define g_T^d as the vector of $L > |\theta|$ identifying moments from the data and the vector $g_{S,T}(\theta)$ as the corresponding moments from the simulated equilibrium where the inclusion of the T and S subscripts remind the reader that these moments may vary across time and, in the case of the model, depend on the total number of simulations S. The estimator then solves

$$\begin{aligned} \hat{\theta} &= \underset{\theta}{\operatorname{argmin}} \left[g_{S,T}(\theta) - g_T^d\right]' A \left[g_{S,T}(\theta) - g_T^d\right] \\ &\textit{subject to} \\ \underbrace{\mathrm{TR}_t^d}_{\substack{\text{Total Revenue} \\ \text{in Data}}} &= \underbrace{\sum_{m \in \{\mathrm{I},\mathrm{F}\}} \sum_{x \in \mathcal{Q}} \mu_t^m(x) p_t^m(x,\mu) s_t^m(x,\mu) M_t}_{\substack{\text{Total Revenue Predicted} \\ \text{by the Model Conditional on } \theta, M, N}} \end{aligned} \tag{10}$$

where

$$g_{S,T}(\theta) \equiv \begin{bmatrix} g_{S,t=1}(\theta) = \frac{1}{S}\sum_{s=1}^{S} \tilde{g}_{t=1}(\theta) \\ \vdots \\ g_{S,t=T}(\theta) = \frac{1}{S}\sum_{s=1}^{S} \tilde{g}_{t=T}(\theta) \end{bmatrix}$$

As $L > |\theta|$ the estimator solves an over-identified system of equations and utilizes the L-by-L positive-definite matrix A to weight the importance of the moments in identifying the elements in θ. To maximize the estimator's efficiency, I construct A using the inverse of the variance-covariance matrix from bootstrapped samples of the data.[19] Equation (10) therefore places more weight on moments which provide better identification of θ. To increase the probability of finding a global minimum to (10), I employed a state-of-the-art minimization software (KNITRO) and repeated

[19] Define N^d as the number of firms in the data set. I construct the bootstrap sample by drawing N^d of these firms with replacement and solving for the vector of moments. I repeat this step 1,000 times.

the minimization from different initial guesses for θ.[20] In practice, the estimator exhibited smooth convergence to the same $\hat{\theta}$ solution.

Solving the Model. Applying the model to the semiconductor industry involves solving for the *Non-stationary Oblivious Equilibrium* for each parameter guess θ. The non-stationary aspect of the equilibrium complicates analysis as it requires solving for the set of period $t = 1, ..., T$ pricing functions, profits, investment rules, and value functions which comprise the equilibrium. I therefore solve the non-stationary equilibrium by assuming there exist two steady-state oblivious equilibria (OE) at either end of the time period in question. The first OE provides the initial firm size distribution while the second OE provides the period T value function.[21] The non-stationary equilibrium I am interested in therefore connects the two stationary OE and therefore amounts to solving a finite-period game as in Goettler and Gordon (2011) and Igami (2017, 2018). Solving the model then amounts to solving for OEs in the initial and terminal periods where the NOE follows by solving the finite-horizon entry and investment problems by backwards-induction.

Solving the model in this way enable me to also simplify the parameter space in two ways. First, I can solve for the NOE as a function of market size M_t and the remaining parameters in θ. Define the following operator which connects predicted market size (*i.e.*, total revenue) and observed market size:

$$M_t^n = M_t^o \times \frac{R_t^d}{R_t(\theta_2, M_t^o)}$$

where R_t^d is the total revenue observed in the data and $R_t(\theta, M_t^o)$ is the industry revenue at market size guess M_t^o. At the fixed point $M_t^n = M_t^o$ the model predicts industry revenue exactly equal to the level observed in the data and the constraint in (10) is satisfied by construction.[22] Second, since I solve the NOE which generates industry revenue consistent with the data given data conditional on the number of firms operating each business model at a point in time, I can recover the value functions associated with entry $\tilde{V}_t^{\mathrm{I}}, \tilde{V}_t^{\mathrm{F}}$. I can then use observed entry rates plus the free entry conditions (5) to solve for equilibrium entry costs $(f_{e,t}^{\mathrm{I}}, f_{e,t}^{\mathrm{F}})$.

Doraszelski and Satterthwaite (2010) prove existence for this class of models, however proving uniqueness is difficult. For example, Besanko, Doraszelski, Kryukov, and Satterthwaite (2010) show that dynamic models based on Ericson and Pakes (1995) are capable of generating multiple equilibria. This is a concern since multiple equilibria would necessarily bias my results in unforecastable ways. Goettler and Gordon (2011) deal with this issue by focusing on equilibria from finitely-repeated games and uniqueness, therefore, occurs if there exists a unique Nash equilibrium

[20] Simulation-based estimators also suffer from simulation bias. I therefore chose the number of simulations S to be sufficiently high (1,000) so such bias is extremely small.

[21] In the first OE the implicit assumption is that not only the industry in a steady-state but also the aggregate demand shock driving the transition to the second steady-state is unexpected and therefore did not affect firm innovation decisions (e.g., Equation 3).

[22] Note that this operator is reminiscent of the mean utility contraction mapping in the discrete choice demand literature, specifically Berry (1994). See also Dube, Fox, and Su (2012) for a discussion connection the constraint in 10 to this contraction operator.

in every subgame (a point which they verify computationally). Here, the transition path amounts to a finite-horizon game but the end points, the OE, are infinite-horizon. Therefore, non-uniqueness could arise in these equilibria and therefore impact the transition path as well. I mitigate this risk by solving the NOE form different initial value guesses for the end-point OE. In practice I find the NOE is resilient to alternative initial guesses. While this does not correspond to a proof of uniqueness it does provide some assurance that multiple equilibria in either the estimation or the counterfactual exercises is not an issue and does not bias the results.

Identification. Identification of θ derives from the role each parameter plays in the model. The marginal utility of money, α, modulates the importance of price in determining demand versus differences in quality. Quality become more important to consumers as $\alpha \uparrow 0$ so high-quality firms enjoy market power and can set high prices to extract consumer surplus. As $\alpha \downarrow -\infty$ just the opposite happens as consumers become increasingly responsive to changes in price and firm market power decreases. Consequently, α is identified by differences in firm profit margins where is I use the gross margin defined as ("total firm revenue minus cost of goods sold" / "total firm revenue") as the data analog to $\frac{p(q)-c}{p(q)}$ where "c" is the firm's marginal cost (*i.e.*, its "cost of goods sold"). These margins are heterogenous in the data as well as in the model so for each period t I compute the average. The price-quality interaction (ω) informs demand elasticities and firm margins across firm quality states. For $\omega > 0$ consumers become less price-sensitive as firm quality increases enabling these firms to charge higher unit markups and the converse is of course true for $\omega < 0$.

Thus, α and ω are identified in the data by firm gross margins across quality states: For a given vector of gross margins in the data, α is identified by the average gross margin while ω is identified the correlation between gross margin and firm quality. As consumer demand implies revenue is increasing in firm quality, ω is also identified the correlation between gross margin and firm revenue. As the compustat data represents audited financial disclosures and contains the universe of IDMs, I focus on matching the the gross margins of these firms. To capture the correlation between gross margin and firm revenue, I define a large (small) IDM as a firm which earns revenue greater (smaller) than the median firm.

The IDM demand shifter (ξ^{I}) is identified by differences in capital expenditure across IDM and Fabless firms via the entry equations (5). As $\xi^{\mathrm{I}} \uparrow 0$ the value of being an IDM increases which implies an increase in the entry cost. In the data this amounts to greater capital expenditure. The identifying data moment therefore is the ratio of Fabless to IDM capital expenditure from Compustat: $\frac{\text{Capex (Fabless)}_t}{\text{Capex (IDM)}_t}$. The accompanying model moment is the ratio of Fabless to IDM entry cost: $\frac{\hat{f}^{\mathrm{F}}_{e,t}}{\hat{f}^{\mathrm{I}}_{e,t}}$. As I do not allow ξ^{I} to vary across time, I compare the sample means from the data and model.

Fabless marginal cost parameters $\{\lambda_t\}$ are identified using the differences in the gross margin of IDM and Fabless firms where we recall that Fabless firms on average have higher margins (Table IV). Thus,

$$\text{IDM Margin} \equiv \frac{p_t^{\mathrm{I}} - 1}{p_t^{\mathrm{I}}} < \frac{p_t^{\mathrm{F}} - \lambda_t}{p_t^{\mathrm{F}}} \equiv \text{Fabless Margin}$$

whenever $\lambda_t < 1$ provided p_t^{I} and p_t^{F} are not too different.

The remaining parameters, $\{w_t^r, \rho\}$, govern the R&D intensity of IDM and Fabless firms across time. Much of this identification can be gleaned by analyzing the solution to the incumbent firm's innovation problem (Equation 3) where optimal R&D effort generates the following decision rule:

$$\begin{aligned} k_t^m(q; \mu_t, M_t) &= \log\left(\frac{V_{t+1}^m(q+\Delta_q; \mu_{t+1}, M_{t+1}) - V_{t+1}^m(q-\Delta_q; \mu_{t+1}, M_{t+1})}{\rho \times w_t^r}\right) \\ \text{s.t.} \quad \mu_{t+1} &= \Upsilon(\mu_t, M_t; k_q, k_{-q}), \; M_{t+1} = \Psi(M_t). \end{aligned} \tag{11}$$

Since I model innovation as an increase (or decrease) in product quality and product quality is a latent variable observable only in deferences in firm revenue, I identify these parameters by the probability IDM and Fabless firms increases their revenue state. For example, 65% of IDMs and 64% of Fabless firms increased their revenues between 1994 and 1995. For the OE equilibria prior to 1990 and beyond 2010, these moments correspond to the likelihood a firm increases its product quality.[23] From (11) we see that an increase in w_t^r decreases the probability firms are successful (*i.e.*, $k_t^m \downarrow$) and equilibrium R&D expense also falls since $c_t^m(k)$ is increasing in k. Similarly, an increase in ρ decreases R&D expense for Fabless firms. Thus, period t innovation cost w_t^r is identified by the percent of firms who successfully increase their relative revenue from period $t-1$ while differences in R&D success rates across IDM and Fabless firms identifies ρ.

In summary, I estimate the model using variation in industry revenue to pin-down changes in market demand, equilibrium value functions to pin-down entry costs, and identify the remaining parameters $\{\alpha, \omega, \xi^{\mathrm{I}}, \rho, w_t^r, \lambda_t\}$ via a Simulated Minimum Distance estimator using identifying moments in the data.

5.3 Estimation Results

I this section I discuss the estimated model. Overall, the estimates are reasonable, statistically significant, and congruent with the descriptive statistics of the semiconductor industry presented in Section 4. In Table V, I present the estimation results for the demand-side parameters alongside their identifying moments. I find that in order to generate gross margins of nearly 50%, the model requires a price coefficient $\alpha = -1.7279$ which is significantly different than zero. At the estimated

[23] Since firms start at $G(q)$ $\forall t = 1, ..., T$ in the model and exit with positive probability, the probability of increasing quality can exceed 50%. I choose the upper bound of the quality ladder such that in expectation the mass of firms which reach the upper bound is very small.

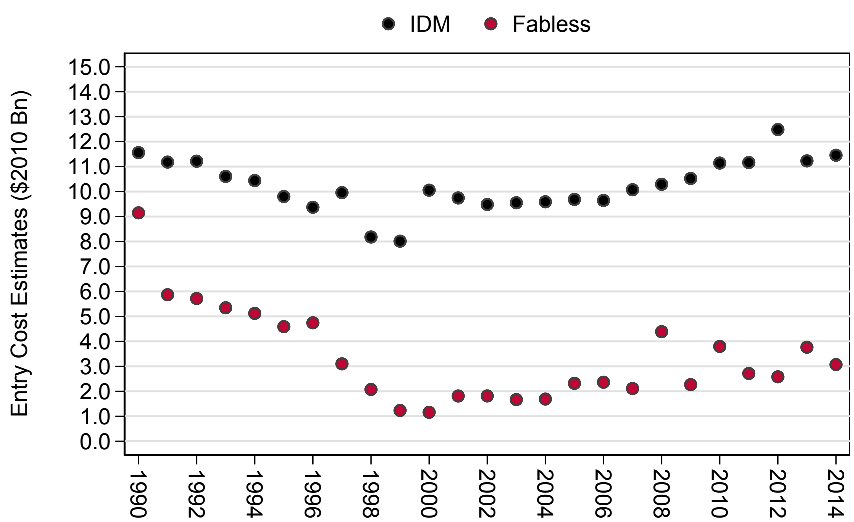
price-quality interaction ($\hat{\omega} = 0.1262$) the model correctly predicts that higher revenue (*i.e.*, higher "quality") IDMs command higher margins though it predicts a much narrower spread between large and small IDMs than observed in the data.

Table V: Estimation Results

Parameter	Value	S.E.	Identifying Moments	Data	Model
Price Coefficient (α)	-1.7279	(0.0334)	Gross Margin (Large IDM)	0.4535	0.4490
Quality Demand Interaction (ω)	0.1262	(0.0089)	Gross Margin (Small IDM)	0.4191	0.4464
IDM Demand Shifter (ξ^{I})	2.8012	(0.0462)	$\frac{\text{Capex (Fabless)}}{\text{Capex (IDM)}}$	0.3176	0.3202

Notes: Statistics for identifying moments correspond to the average over the periods in the sample. "Deviation" corresponds to the average percent deviation across periods of the model's prediction and the observed value in the data for each identifying moment.

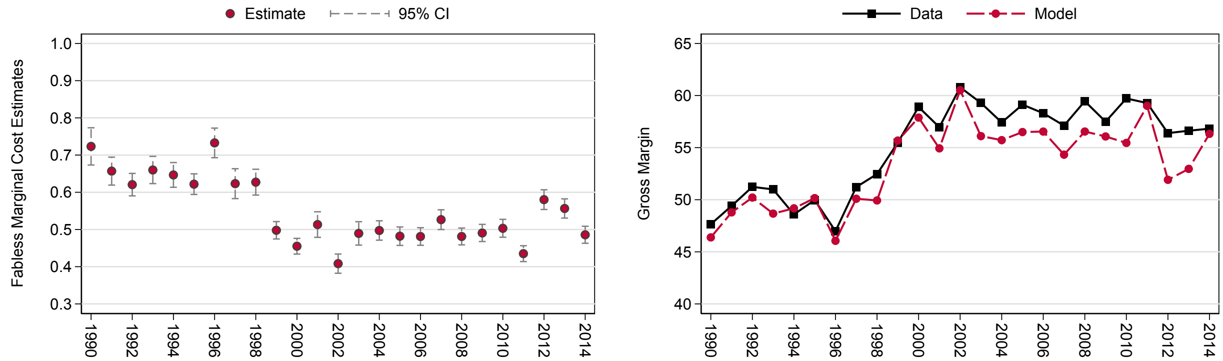
Figure 3: Estimated Entry Costs: $\hat{f}^{\mathbf{I}}_{e,t}, \hat{f}^{\mathbf{F}}_{e,t}$



Notes: Points correspond to the estimated entry costs implied by free-entry condition (5). Bars correspond to the 95/5 confidence interval which are calculated via bootsrap using the estimated standard errors of $\hat{\theta}$.

In Figure 3, I present the estimated entry costs implied by the model. We observe that entry costs for both firm types are significant but that entry costs for Fabless firms are much less than for the IDM. In the data this is due to the fact that Fabless firm can avoid the expensive capital outlay to build a fabrication facility and this difference materializes in lower capital expenditure per firm. In the model this is captured by the combination of the number of firms of each business type plus the IDM demand shifter $\hat{\xi}^{\text{I}}$ via the entry equations (5). Interestingly, the difference between entry costs across the firm types is growing as time progresses. This could be due to technological improvements which reduced coordination costs of outsourcing firms (Fort, 2015).

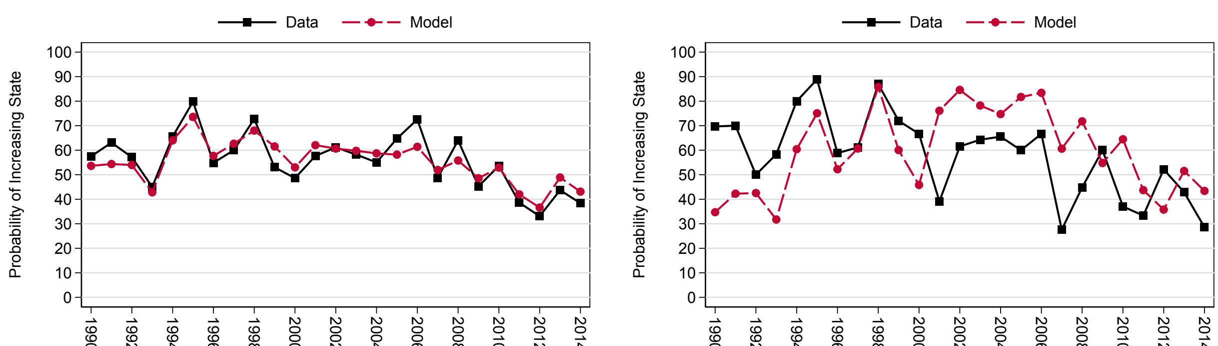
Figure 4: Model Fit: Fabless Gross Margin



(a) Fabless MC $\{\hat{\lambda}_t\}$ (b) Fabless Gross Margin

In Figure 4 I present the estimated Fabless marginal costs ($\hat{\lambda}_t$) in Panel (a) alongside the identifying gross margins (Panel b). As with the estimates of Table V, the model is sufficiently flexible to replicate the margins observed in the data across the sample. In Figure 5 I document the model fit of IDM (panel a) and Fabless (panel b) R&D success rates. In panel a we observe that the estimator chooses research costs w^r_t to correctly replicate the success rates across time though the estimated values generate slightly less-volatile success rates than the data. In panel b we observe that the estimated value of $\hat{\rho} = 0.0554$ implies Fabless research costs significantly lower than for IDM firms and generates R&D success rates which are similar to the data though more noisy than in the IDM case.

Figure 5: Model Fit: R&D Success



(a) IDM Firms ($\hat{w}^r_t$) (b) Fabless Firms ($\hat{\rho}$)

6 Why do Firms Outsource Production?

In this section I use the estimated model to evaluate the factors which drive firms to outsource production. Underlying this analysis lie the model's entry conditions which I repeat here for clarity:

$$\begin{aligned}
\Pr_t^{\mathrm{I}}(\text{entry}) &= \frac{exp(\tilde{V}_t^{\mathrm{I}} - \hat{f}_{e,t}^{\mathrm{I}})}{1 + exp(\tilde{V}_t^{\mathrm{I}} - \hat{f}_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}} - \hat{f}_{e,t}^{\mathrm{F}})} \\
\Pr_t^{\mathrm{F}}(\text{entry}) &= \frac{exp(\tilde{V}_t^{\mathrm{F}} - \hat{f}_{e,t}^{\mathrm{F}})}{1 + exp(\tilde{V}_t^{\mathrm{I}} - \hat{f}_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}} - \hat{f}_{e,t}^{\mathrm{F}})}
\end{aligned}$$

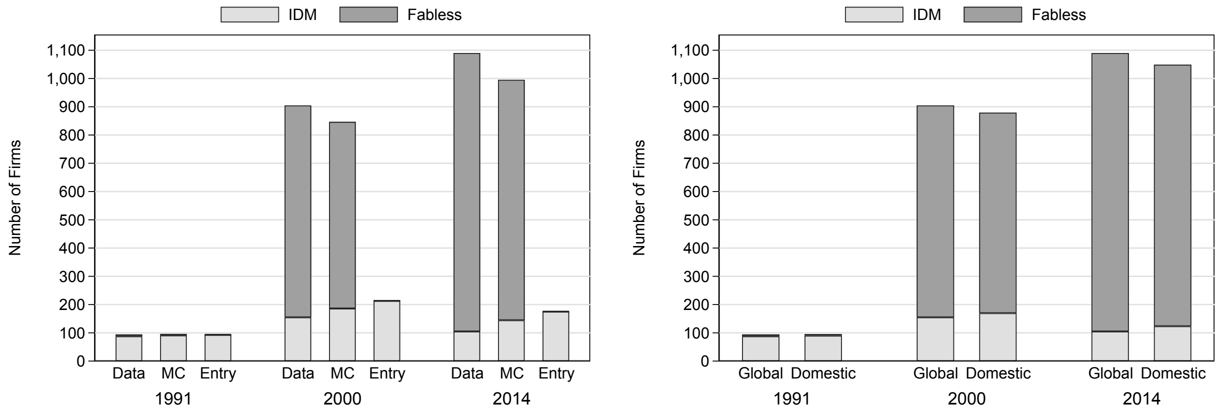
Any factor which increases the value of being a Fabless firm (V_t^{F}), decreases the entry cost of creating a Fabless firm ($f_{e,t}^{\mathrm{F}}$), or decreases the value of becoming an IDM ($\tilde{V}_t^{\mathrm{I}}$) will increase the likelihood that the $\mathcal{N}_t$ prospective entrants choose to introduce a Fabless firm. The estimated model therefore provides a framework to evaluate the quantitative importance of each of these channels. In so doing, it provides insight into the relative importance of several hypotheses as to the drivers of outsourcing. I do so by comparing the estimated equilibrium to several counterfactual equilibria where for each I resolve the non-stationary equilibrium holding other factors constant, including market size ($\hat{M}_t$). My analysis therefore enables me to isolate and evaluate a particular aspect of the estimated model. This approach is similar to a comparative statics analysis one might apply to a theoretical model which admits analytical equilibrium solutions.

In Figure 6 I evaluate the extent to which differences in entry and production costs can explain the growth in outsourcing. In panel (a) I compare the firm composition across two scenarios. First, I equalize production costs by setting $\lambda_t = 1\ \forall t$ but I leave entry costs at their estimated levels ("MC"). Second, I equalize entry costs by increasing the period t Fabless entry cost to the estimated IDM entry cost $\hat{f}_{e,t}^{\mathrm{F}} = \hat{f}_{e,t}^{\mathrm{I}}\ \forall t$ but I leave Fabless production costs at their estimated levels ("Entry"). This experiment simulates the effect of off-shoring where the firm still builds, owns, and operates a fabrication facility and locates the plant overseas to take advantage lower production costs.

Modifying either the Fabless entry or production costs early in the sample has little effect on the industry as outsourcing was uncommon. As time passes, the market grows and outsourcing becomes more popular, however, an increase in production costs leads to less market entry overall as less entering firms choose to outsource production though some firms that would have outsourced production nonetheless enter as IDMs. The effect on the industry is more stark when I equalize entry costs, or equivalently when firms can only offshore production: Increasing the Fabless entry cost to the estimated levels of IDM firms effectively eliminates Fabless firms. Thus, while outsourcing is popular in the estimated model and accounts for roughly one-third of industry revenues, I find no scope for offshoring in this industry.

In panel b, I evaluate the role of global supply chains on composition of firms in this industry. I do so by adjusting the production cost advantage afforded to Fabless firms to eliminate

Figure 6: Cost as a Mechanism to Explain Outsourcing



(a) Production vs Upfront Costs

(b) Global Supply Chain

the gains of overseas production found in Table III.[24] The results indicate that outsourcing does decrease when we remove overseas markets but the effect is not dramatic. Thus, outsourcing in this industry is not solely motivated by factors which drive global supply chains such as reductions in transportation costs or import tariffs.

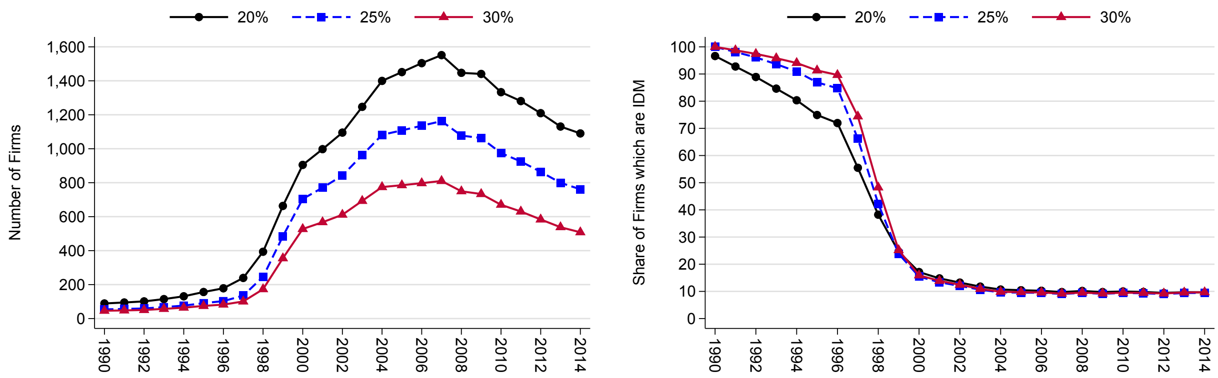
Thus far I have treated the estimated entry costs as a primitive while in reality they represent a variety of inputs required to establish a firm, including financing where venture capital has traditionally played a significant role. Interestingly, growth of the semiconductor industry, and particularly of the Fabless business model, is closely-aligned with growth of the venture capital industry as the latter enables financing and operational expertise to start-ups.

In Figure 7 I evaluate how changes in the venture capital industry could have impacted the semiconductor industry. I do so via the interest rate charged to the prospective entrepreneur thinking of starting either an IDM or Fabless firm in period t where I assume the entry costs amount to the discounted present value of future capital expenditure. Under the estimated model, I decompose the estimated entry costs into actual capital expenditure (*i.e.*, money spent on buildings and equipment) and interest expense where I assume a 20% interest rate. I therefore simulate an increase in the entry costs of firms (both IDM and Fabless) by increasing the interest rate to 25% and 30% which increases entry costs.

An increase in the financing rate decreases the number of firms in the industry significantly indicating the industry's sensitivity to changes in start-up costs and reliance on financing channels such as venture capital (panel a). While the increased financing cost decreased firm entry and consequently the equilibrium number of firms in the industry, the fact that both IDM and Fabless firms are financed through venture capital had little impact on the changing composition of firms

[24] Recall that in Table III I used to the detailed wafer pricing data to show that outsourcing production to an overseas firm (e.g., Taiwan Semiconductor) represented a 26.95% reduction in cost relative to outsourcing to a US firm. In columns marked "Domestic" I resolve the non-stationary equilibrium when Fabless production costs are $\tilde{\lambda}_t = \hat{\lambda}_t/(1 - 0.2695)$.

Figure 7: The Role of Venture Capital Funding



(a) Number of Firms (b) IDM Share

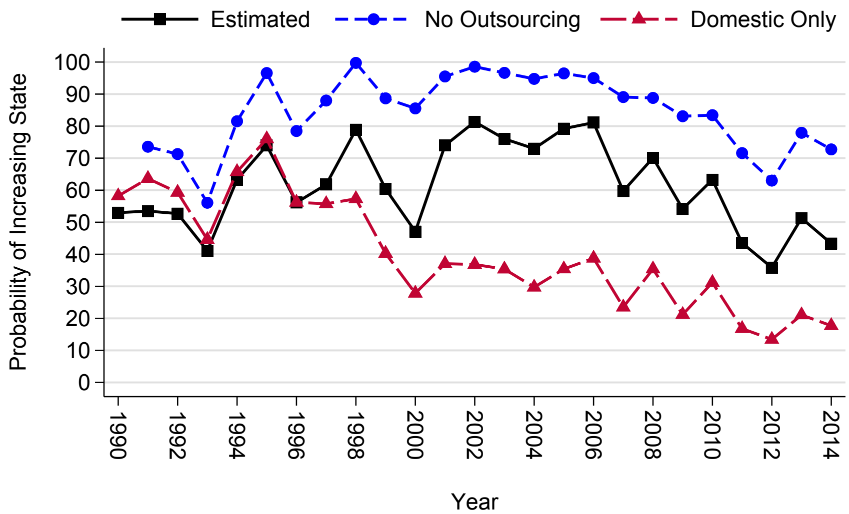
(panel b). Interestingly, at financing costs the growth of Fabless firms, as a percent of total, is slower than in the estimated model at the beginning of the 1990s but accelerates at the end of the 1990s to reach the same steady state level by 2000.

7 Outsourcing and Firm Innovation

In this section I use the estimated model to evaluate the impacts of outsourcing, *i.e.*, of Fabless production, on the evolution of the semiconductor industry. As before, I hold consumer market size ($\hat{M}_t$) fixed. This implicitly assumes that changes in outsourcing behavior and the subsequent equilibrium changes in semiconductor prices have no impact on retail consumer demand for products enabled by semiconductors. I also hold entry costs ($\hat{f}_{e,t}$) fixed which assumes there are no market scale effects of technological spillovers from entry. I evaluate the effects of outsourcing on incumbent firm innovation by comparing the R&D success rates of two counterfactual experiments to the estimated model (*i.e.*, "Estimated"). In "No Outsourcing" I eliminate outsourcing by setting $f^{\mathrm{F}}_{e,t}$ sufficiently high to make Fabless firm entry close to zero. In "Domestic Only" I change Fabless production costs to simulate shutting down overseas production as in the "Domestic" equilibrium in Figure 8.

I find that eliminating outsourcing leads to greater firm R&D throughout the sample (Figure 8). This is because eliminating Fabless firms decreases competition and increases IDM profits leading to greater R&D investment from these firms (Figure 12). From the "Domestic Only" line we observe the equilibrium impact of outsourcing production overseas as the estimated model yields greater overall firm innovation (R&D success). Here, lower fabrication costs abroad increase Fabless firm profits leading to more research and a greater probability of success (Figure 13). While the ability of Fabless firms to source from abroad does increase their competitive positioning relative to IDM firms leading to lower IDM profits and less research expense (Figure 12), the effect is small due to the horizontal differentiation of IDM products (*i.e.*, $\hat{\xi}^{\mathrm{I}} > 0$).

Figure 8: Outsourcing and Incumbent Firm Innovation



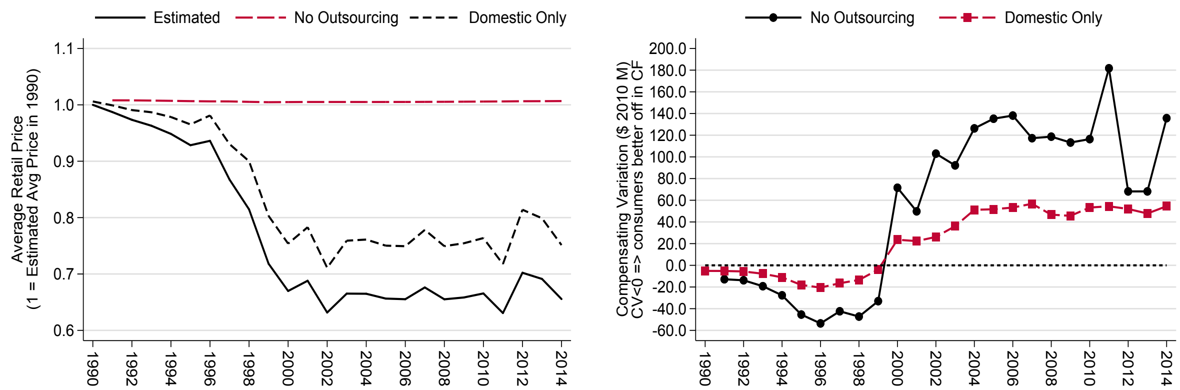
These results provide empirical evidence to a long-standing question in empirical industrial organization: Does competition foster or inhibit innovation? In "The Theory of Economic Development" Joesph Schumpeter hypothesized that increased competition actually decreased innovation by reducing firm profits and therefore the ability to finance or incentivize research and development. My results indicate that the increased competition enabled by outsourcing, at least in this industry, reduced the incentive to innovate among incumbent firms.

Thus far I have shown that outsourcing in the Semiconductor industry relaxed a liquidity constraint by enabling smaller, less-valuable firms to enter the industry. The ability to outsource production overseas was an important but not vital ingredient to the success of the Fabless business model, or to outsourcing more generally. Ultimately, increased entry of Fabless firms lead to lower incumbent firm innovative effort, however. I conclude this section by combining these results to ask whether outsourcing made this industry more dynamically efficient: *i.e.*, Did outsourcing increase consumer welfare?

In Figure 9 I compare equilibrium average price (panel a) consumer compensating variation (panel b) where the calculation of the latter utilizes the familiar log-sums formula for consumer surplus and the estimated price coefficients $(\hat{\alpha}, \hat{\omega})$ plus the estimated market size $(\hat{M}_t)$. From panel (a) we see that prices in the estimated model (solid black line) are generally falling across the sample as increased entry of Fabless firms decreases average industry price. Eliminating outsourcing all-together generates largely static pricing as IDMs change their prices little across time in the model. Restricting Fabless firms to utilize only domestic production mutes the entry of Fabless firms and consequently the evolution of firm prices.

The effects on consumer welfare are more varied. Throughout much of the 1990s when Fabless firms were less common (Figure 1, panel b), entry of Fabless firms reduced IDM profits and incentive to innovate (Figure 12) leading less and lower-quality firms (products). The result for consumers is that eliminating outsourcing or even just limiting domestic firms to provide outsourced

Figure 9: Outsourcing, Global Supply Chains, and Welfare



(a) Average Price (b) Consumer Surplus

Notes: In panel (a) I present percentage change in average retail price as I modulate the production cost of outsourcing. In panel (b) I present the implied consumer surplus implied by equilibrium relative to estimated equilibrium in the data.

fabrication services would have increased welfare. As the market continued to grow and outsourcing became more popular, the growth in varieties came dominate these effects leading to a net increase in consumer welfare. These results are interesting as they demonstrate that welfare along the transition path may be negative as an industry re-allocates resources but nonetheless the long-term welfare benefits are positive. They also serve as empirical evidence that effective government policy must not only address near term but also long-term effects since a benevolent but myopic government in the 1990s might have been tempted to institute policy to shut-down outsourcing thereby limiting the ultimately beneficial impact that outsourcing had on the industry.

8 Conclusion

In this paper I addressed the equilibrium effects of outsourcing on the evolution of the semiconductor industry. I did so by developing a dynamic oligopoly model of innovation in which firms strategically outsource production overseas and invest to increase the quality of their product. To account for exogenous market growth I consider firm strategies which vary over time as the market grows and transitions between steady-states. I then estimated the model using detailed data from the semiconductor industry – an industry in which outsourcing has become a significant business model. The estimated model replicates moments in the data well and generates reasonable and statistically significant parameter values.

I show that growth of outsourcing was largely due to the ability of firms to avoid the large cost of building a fabrication facility rather than lower production costs due to economies of scale from third-party facilities. I also find that the industry's evolution is sensitive to changes in the venture capital industry which would have impacted financing rates and therefore capital expenditure costs. These results indicate that outsourcing amounted to a new financial technology which decreased entry costs and enabled entry of smaller companies. Increased entry of Fabless firms ultimately led to increased competition for the traditional, vertically-integrated IDMs leading to less profits for these firms and ultimately less innovative effort. Consumer welfare along the transition path is negative early but becomes positive as the industry approaches the long-run steady-state. Thus, my results indicate that outsourcing improved the dynamic efficiency of the industry by enabling entry of new firms and that effective government policy requires a long-run perspective.

While the model captures many of the important characteristics of the industry, there are potential avenues for improvement. Including research spillovers as in Goettler and Gordon (2011) and endogenizing the effective labor wage rates may have important equilibrium effects and are areas for further research.

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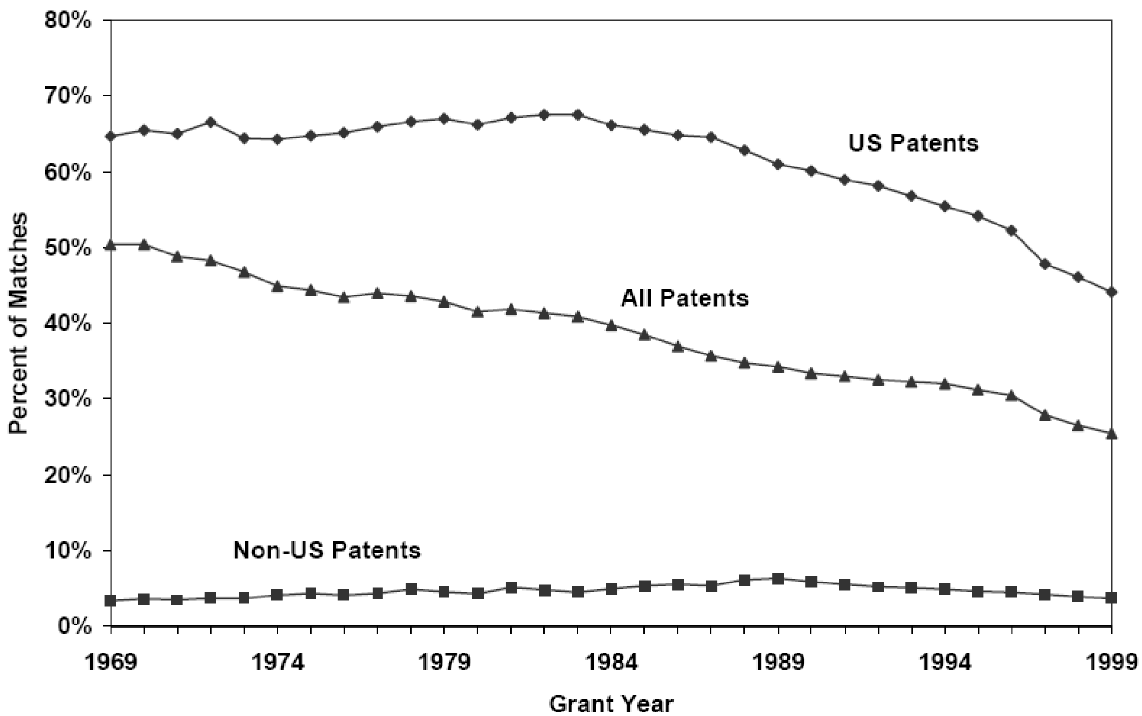
A Data Sources

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. 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 (2001) – in which patent grant data from the USPTO was matched with Compustat CUSIP identification. The match was based on the assignee names in the USPTO data and the list of firm names in Compustat.

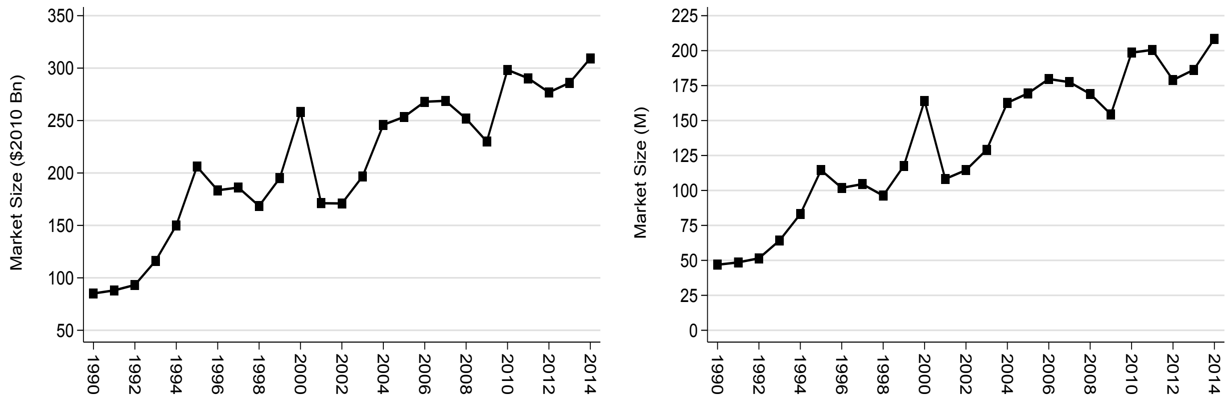
Figure 10: Compustat Match Rate



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.

B Other Results

Figure 11: A Growing Market



(a) Total Industry Revenue

(b) Consumers ($\hat{M}_t$)

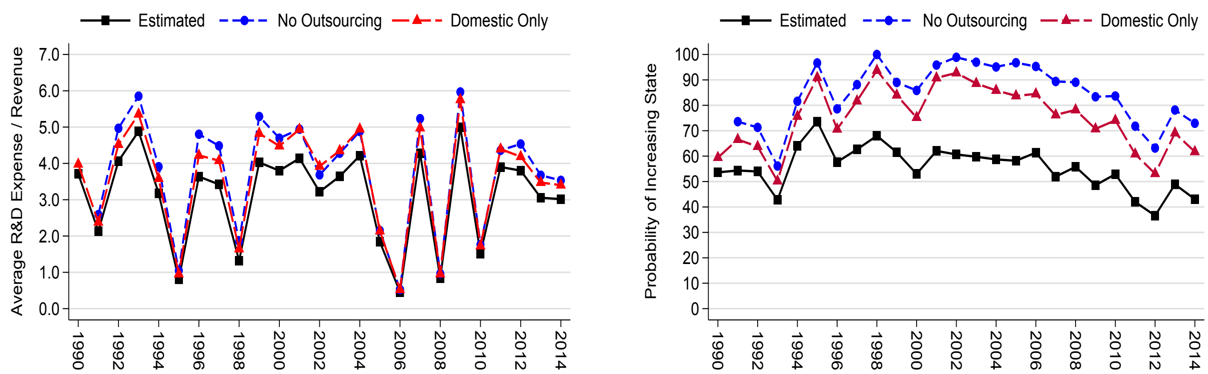
Source: In panel a, I present growth in industry revenue (source: WSTS Semiconductor Market Forecast Autumn 2017). In panel b, I present the estimated number consumers required to generate the observed industry growth.

Table VI: The Foundry Market

Company	Type	Country	Revenue ($M)	% of Total
1. TSMC	Pure-play	Taiwan	13,332	46.67
2. UMC	Pure-play	Taiwan	3,824	13.39
3. GlobalFoundries	Pure-play	United States	3,520	12.32
4. SMIC	Pure-play	China	1,554	5.44
5. Dongbu HiTek	Pure-play	South Korea	512	1.79
6. TowerJazz	Pure-play	Israel	509	1.78
7. Vanguard (VIS)	Pure-play	Taiwan	505	1.77
8. IBM	IDM	United States	500	1.75
9. MagnaChip	IDM	South Korea	410	1.44
10. Samsung Semiconductor	IDM	South Korea	390	1.37
Others	-	-	3,510	12.29
Total	-	-	28,566	100.00

Source: Gartner. "Pure-play" foundries are fabrication plants in which all production is of chips designed by other companies. "IDM" foundries are internal fabrication facilities. In 2015 IBM exited the foundry business and sold its operations to GlobalFoundries.

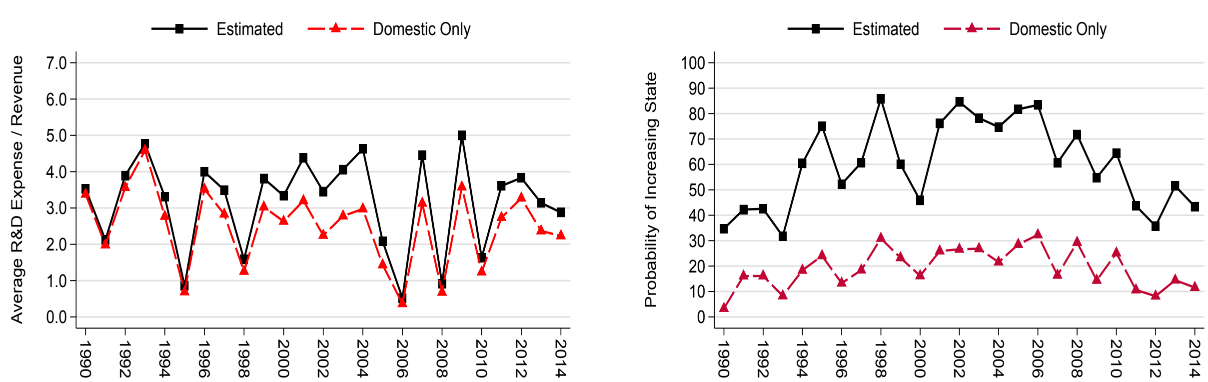
Figure 12: Outsourcing and Incumbent IDM Innovation



(a) Research Expense as a Percent of Revenue

(b) R&D Success Rate

Figure 13: Outsourcing and Incumbent Fabless Innovation



(a) Research Expense as a Percent of Revenue

(b) R&D Success Rate