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

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PRELIMINARY

Abstract

I build a dynamic oligopoly model to identify the factors which explain the increase in factoryless production in the global semiconductor industry. Firms enter the industry each period and choose whether to invest in developing proprietary fabrication facilities or instead outsource production to a competitive third-party fabrication industry. The estimated model demonstrates that factoryless production enables firms to significantly reduce upfront capital expenditure thereby lowering the costs of entry. The increasing availability of venture capital investment also played an important role, while the possibility of growth through future R&D investment and the benefits of lower production costs, due to sourcing either domestically or globally, had little impact on equilibrium entry. Factoryless and integrated firms co-exist in the long run equilibrium since the latter firms are able to vertically differentiate their products, enabling them to maintain significant market share despite significant entry of factoryless firms.

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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 (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 that 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 entry and exit decisions of firms and the subsequent evolution of the industries they inhabit, is not well understood, however.

I study the impact of sourcing on firm entry and exit in the semiconductor industry – an industry which produces goods (e.g., microprocessors) which enable nearly every facet of our modern digital 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.[1] 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 90% all semiconductor firms and generate one-third 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, often overseas, enables these firms to take advantage of scale to lower input costs as they pool production with other Fabless firms in third-party foundries. Outsourcing overseas also enables

[1] 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.

firms to reduce take advantage of lower foreign wages and weaker environmental standards. 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. Consequently, it is unclear whether there exists a clear dominant business strategy, IDM or Fabless, in the long-run; or perhaps the two can 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 in which firms strategically choose whether operate in-house fabrication facilities or outsource production to a perfectly-competitive third-party fabrication industry. To account for changing exogenous upfront entry costs, on-going production costs, and industry growth; I consider firm strategies which vary over time as the industry transitions between long-run equilibria. Therefore, the equilibrium concept I adopt is a non-stationary modification to the Moments-based Markov Equilibrium (MME) of Ifrach and Weintraub (2016). In a MME, firms have limited capacity to monitor the entire distribution of rivals and instead focus on a few sufficient statistics. In a non-stationary MME (nMME) I maintain this assumption but allow for the industry to transition between two long-run MME equilibria. The first MME provides a starting point for the initial industry state while the second stationary MME provides firms information for their long-run value function. Importantly, the second stationary MME need not be contained in the data but can rather occur at an arbitrary future date provided one is willing to assume that model primitives which had induced the transition are fixed, or equivalently are growing at a constant rate.

In the first stationary MME the implicit assumption is that not only is the industry in a stationary MME but also that the changes in the industry which drive the transition to the second stationary MME are unexpected. In my setting this is the establishment of the first "pure play" foundry, Taiwan Semiconductor Manufacturing Company (TSMC), by Morris Chang in 1987. Chang, a Ph.D. electrical engineer trained at Stanford, had risen through the ranks at Texas Instruments, one of the largest IDMs, until ultimately becoming head of all semiconductor operations at the company. At a time when most people might have considered retirement, he was recruited by the Taiwanese government to found TSMC with the intent of boosting the country's high-tech sector in order to compete with firms in Japan and the United States.

Unitl TSMC's founding, innovation appeared to be limited as entrepreneurs equipped with good ideas lacked the immense capital required to make their designs a reality:

> When I was at TI and General Instrument I saw a lot of IC designers wanting to leave and set up their own business, but the only thing, or the biggest thing that stopped them from leaving those companies was that they couldn't raise enough money to form their own company. Because at that time it was thought that every company needed manufacturing, needed wafer manufacturing, and that was the most capital intensive part of a semiconductor company, of an IC company. And I saw all those people wanting

> to leave, but being stopped by the lack of ability to raise a lot of money to build a wafer fab.

Furthermore, the location of TSMC in Taiwan played to the country's comparative advantage:

> We had no strength in research and development, or very little anyway. We had no strength in circuit design, IC product design. We had little strength in sales and marketing, and we had almost no strength in intellectual property. The only possible strength that Taiwan had, and even that was a potential one, not an obvious one, was semiconductor manufacturing, wafer manufacturing. And so what kind of company would you create to fit that strength and avoid all the other weaknesses? The answer was pure-play foundry.

This speaks to the changing role of the boundary of the firm enabled by international trade (Atalay, Hortaçsu, Li, and Syverson, 2017). In the model, I treat the Taiwanese government's to develop TSMC as an exogenous and unforeseen (to the rest of the IDM semiconductor firms) shock in the industry.

The model serves two purposes. First, I use it as a theoretical framework to identify four potential channels which drive outsourcing. First, 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. Second, I show 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). Third, outsourcing overseas to take advantage of lower variable costs (e.g., wages) further increases the expected value of entry. Finally, if Fabless firms are able to lever their reduced capital expenditure and lower marginal costs to invest in research and design, future growth opportunities may be brighter for an outsourcing firm relative to a vertically-integrated IDM.

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.[2] For an incumbent firm, the model predicts that, all else equal, an increase in discounted profits due to outsourcing increases the willingness to stay in the market.

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 proprietary data from the semiconductor

[2] 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.

industry, including detailed wafer pricing data which enable 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 the 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, either domestic or abroad, or future growth possibilities from conducting research. 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.

Finally, I use the estimated model to forecast the long-run evolution of the industry. I show that vertical-differentiation between IDM and Fabless firms enables the two business models to co-exist. The long-run industry equilibrium is therefore best characterized as one in which IDMs account for only 20% of semiconductor firms though they generate 60% of industry revenue.

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 three 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, firms produce differentiated goods in this industry (and in the model) which provides for the long-run co-existence of both IDM and Fabless firms. Third, my objective is to use the estimated model to evaluate the relative contributions of each channel towards explaining the relative roles each played. This also enables me to identify an important mechanism which further increased market entry of these firms: venture capital. This is an important finding since there exists few empirical studies in the literature which quantify the merits of the venture capital industry despite the fact of its omnipresence in innovation epicenters such as Silicon Valley, CA and Seattle, WA.

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).[3]

In the semiconductor industry, early studies focused on the patenting motives[4] 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.[5]

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

The remaining paper is structured as follows. In Section 2, I present information about the global Semiconductor industry and discuss important defining features of the data. In Section 3, I present the dynamic oligopoly model and discuss how I extend the MME to a non-stationary setting. Section 4 provides details on the estimation and presents the estimation results. In Section 5, I use the estimated model to measure whether the increase in factoryless production was due to reductions in upfront costs; lower on-going production costs due to sourcing from either domestic or global third-party facilities; or future growth prospects from investments in research & design. I also discuss the long-run equilibrium implications of factoryless production in this industry. I provide concluding remarks and discuss areas for further research in Section 6.

[3] See Berry and Compiani (2017).

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

[5] 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.

2 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[6] 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.[7] 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 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.[8] 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

[6] 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).

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

[8] 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.

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.

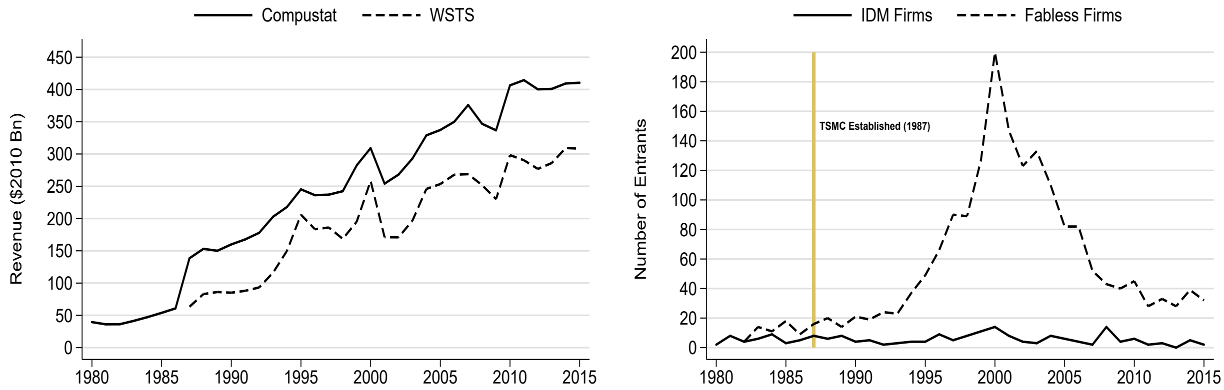
Comparative advantage comes through innovation and innovation is a fast-paced, cumulative effort in which tomorrow's new product depends heavily on a broad set of today's products and ideas. In a 1965 paper, Intel co-founder Gordon E. Moore noted that the capabilities of the integrated circuit doubled roughly every 18 months.[9] This prediction became known as "Moore's 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.

2.1 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 6 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-third of all industry revenue is generated by fabless firms. In panel (b) I document the dramatic increase in Fabless entry after the establishment of TSMC, particularly in the later 1990s. Whereas nearly every firm prior to TSMC's establishment was vertically-integrated, 90% of all firms today are Fabless – a dramatic shift.

[9] 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: A Growing and Changing Industry



(a) Total Industry Revenue

(b) Firm Entry

Notes: In panel a, I present total industry revenue over time using two different approaches. In the solid line I present the time series based on Compustat financial information for firms identifies as semiconductor firms by the Global Semiconductor Alliance. In the dashed line I present the time series based on industry equity analysts (source: WSTS Semiconductor Market Forecast Autumn 2017). In panel b, I present the time series of firm entry for IDM and Fabless firms (source: Global Semiconductor Alliance).

2.2 An International Market for Semiconductor Fabrication

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.

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

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).

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.[10]

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.

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)

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

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 *** $p < 0.01$.

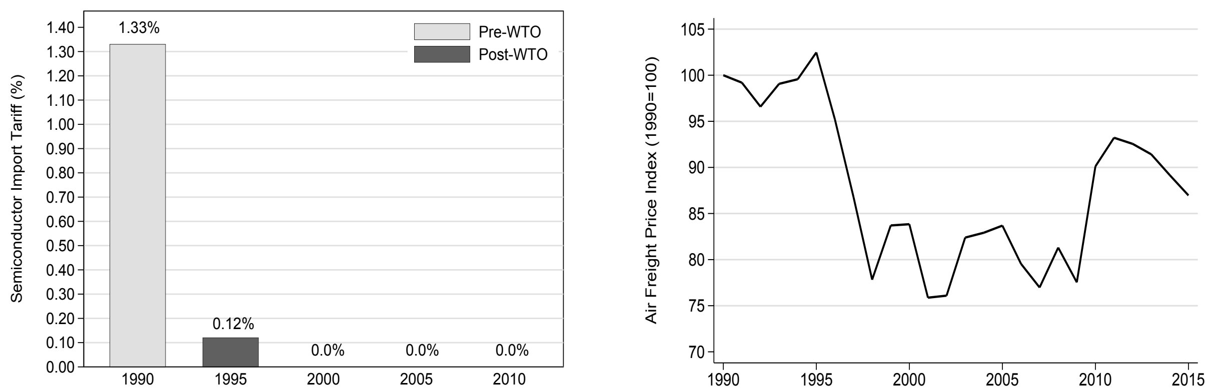
and suggests TSMC actually charges a higher price relative to U.S. foundries. In the remaining columns I include covariates for product characteristics as well as product-level fixed effects which I define as the process size and wafer size pair.

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.

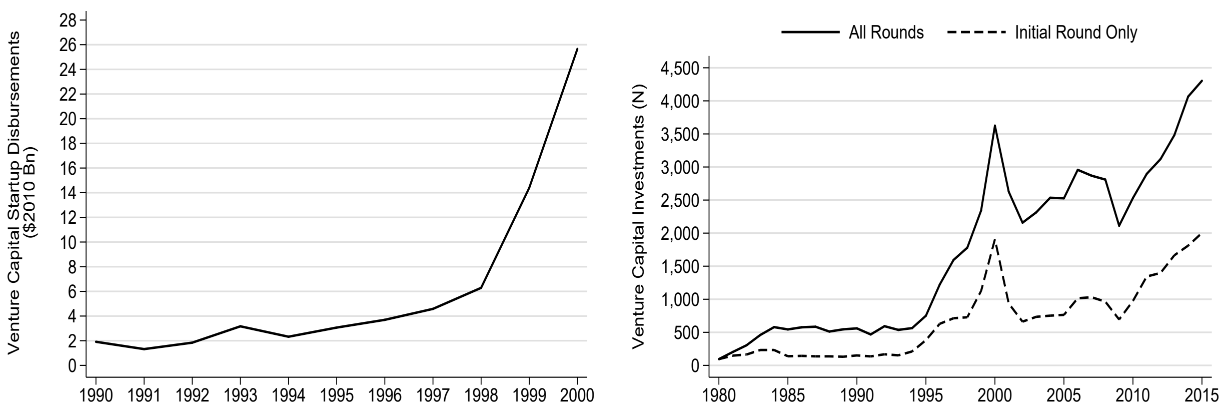
In Figure 2 I show that the semiconductor industry benefited from both of these effects. In panel (a) we see that import tariffs for semiconductors fell to zero after the implementation of the Uruguay Trade round – the same trade round which created the World Trade Organization. In panel (b) we see that 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.

2.3 A Role for Venture Capital

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 may not be practically infeasible. This is a similar argument put forth by Morris Chang when he was asked for the motivation behind founding TSMC.

While funding an IDM may require significant investment to enable construction of a fabrication facility, Chang's argument that third-party foundries can enable new ideas to avoid this step and gain funding elsewhere. In Figure 3, I present statistics about the venture capital industry – an industry which proved to be a primary funding source of Fabless firms. We observe that both in terms of value and number of deals, the venture capital industry grew significantly around the time the Fabless business model gained significant popularity. While this relationship was likely beneficial for both industries, it suggests that the venture capital industry may have played a critical role in securing funding for Fabless firms.

Figure 3: The Growth of Venture Capital



(a) Total Investments

(b) Number of Semiconductor Investments

Notes: In panel a, I present venture capital investments during the beginning of the sample (source: NSF Science & Engineering Indicators, 2002). In panel b, I present the number of investments made by venture capital firms in technology-oriented industries, including semiconductors. (source: Refinitiv).

2.4 Financial Performance Across Business Models

In Table IV I compare characteristics of IDM and Fabless firms. As noted earlier, entry of of Fabless firms far out-paced IDM entry leading to a greater number of these firms in the marketplace. Fabless firms are also more likely to be privately-owned (17% vs. 37%), expend roughly half as much of their sales revenue on capital expenditure, and have enterprise values much lower than IDMs. Like IDMs, however, they tend to be headquartered in the United States, Taiwan, and China.

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, Fabless and IDM firms invest 9.2% and 6.1% of sales 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.

Table IV: Summary Statistics for Fabless and IDM Firms

	Fabless	IDM
Governance:		
Number of Firms (2014)	1,046	267
% Public	17.21%	36.70%
Headquarters	1. USA (38.2%) 2. Taiwan (12.35%) 3. Japan (11.61%) 4. China (9.73%) 5. Germany (5.24%)	1. USA (35.75%) 2. China (17.3%) 3. Taiwan (15.96%) 4. Israel (4.97%) 5. UK (3.82%)
Financial Performance:		
Gross Margin ($\frac{\text{Revenue}-\text{COGS}}{\text{Revenue}}$)	44.02%	38.84%
Capital Expense / Revenue	8.12%	15.34%
R&D Expense / Revenue	9.19%	6.10%
% Rev. Increase	60.11%	58.67%
Enterprise Value ($M)	1,192.07	2,555.50

Notes: Upper panel based on information from the Global Semiconductor Alliance. Lower panel financial statistics based on financial disclosures of publicly-held Fabless and IDM firms.

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 ($R_{j,t}$). To isolate improvements in revenue relative to the competition from increases in overall market revenue (Figure6, Panel a), I evaluate the percent of firms who successfully increase their competitive position (*i.e.*, "% Rve. Increase") as follows: 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.*, $\frac{R_{j,t}}{\overline{R}_t} < \frac{R_{j,t+1}}{\overline{R}_{t+1}}$. Based on this metric, research efforts of both firm types are generally successful and there little exists variation across the sample.

3 Theory

In this section I present the model for the semiconductor industry. The model builds on the dynamic oligopoly framework of Ericson and Pakes (1995). Time is discrete and infinite. Each period t is labeled $t = 1, 2, \ldots, \infty$. In a given period there n_t incumbent firms of which n_t^I are IDMs and n_t^F are Fabless. Each incumbent firm is assumed to produce a single product and firms are heterogenous in the "quality" of their product where a product of a higher "quality" increases demand for the firm's product. Thus, product "quality" captures vertical-differentiation in the industry.[11] In each period t incumbent firms choose price to maximize static, one-period profits taking into account the distribution of of product qualities among competing firms (μ_t) as well as the demand of M_t heterogenous, utility-maximizing consumers. For simplicity, I assume that consumers are myopic. I define the industry state as $s_t = (\mu_t, M_t)$.

The industry evolves according to the following timing: (1) Each incumbent firm i enters period t with knowledge of its product quality x_i and receives a non-negative real-valued sell-off value ϕ_{it} that is private information and is independently and identically distributed using a well-defined density function with finite moments. (2) Firms simultaneously set their product prices taking into account the industry state $s_t = (\mu_t, M_t)$ and profits are realized. (3) Firms compare their private sell-off values with the value of remaining in the industry. If the sell-off value exceeds the value of remaining in the industry, the firm chooses to exit and earns the sell-off value. Exiting firms cease to exist permanently and do not consider any option value of re-entry. (4) Surviving firms transition to a different product quality state similar to the quality-ladder process of Goettler and Gordon (2011) though for simplicity I assume this transition is exogenous. At the same time, entrepreneurs create new IDM and Fabless firms taking into account the future evolution of the industry. The industry state therefore changes to s_{t+1}.

The equilibrium concept commonly applied in this type of dynamic oligopoly model is that of the symmetric pure strategy Markov perfect equilibrium (MPE) of Maskin and Tirole (1988), where period t firms to condition their behavior upon full knowledge of the industry state, particularly the distribution of firm types μ_t. The limitation of the MPE concept is that it requires that firms have a lot of information about the competition (*i.e.*, they know μ_t) which ultimately implies that the possible industry states a firm must consider when addressing the dynamic consequences of its move grows quickly in with both the number of firms and the number of potential states a firm can occupy. For the researcher, MPE is a limitation which enables analysis of only industries with few players (e.g., Collard–Wexler, 2013). More generally, if we believe that in larger industries our models do indeed capture the strategic interactions among many firms, MPE seems to be an unrealistic approximation of firms' information sets.

As computing the MPE for an industry populated by hundreds of firms is both intractable and likely unrealistic, I instead restrict firm information sets to account for only sufficient statistics

[11] In the data firms produce many products so product "quality" amounts to an aggregation across the firm's product portfolio.

from the distribution μ_t as in the moments-based Markov Equilibrium (MME) of Ifrach and Weintraub (2016).[12] Moreover, since my interest is in identifying the economic mechanisms underlying the increase in fabless production, I generalize MME to account for non-stationary transition dynamics.

3.1 Spot Market Equilibrium

I begin by discussing the period t equilibrium consumer demand, firm prices, and firm profits conditional on the firm composition of the industry. Each firm produces a single product r of quality x. 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. 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.

Consumer Demand. Consumer demand follows the large literature of discrete choice in the Industrial Organization literature, though "consumers" in those models are often thought of as human beings whereas the term "consumer" here is best thought of as a downstream technology company (e.g., Lenovo).[13] 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" x among the products. There is no storage so the consumer's optimization problem is static.[14]

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

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

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

[12] Whereas Ifrach and Weintraub (2016) demonstrate that MME can serve as a good approximation to MPE, I am assuming that firm behavior is best captured by the usage of sufficient statistics to keep track of μ_t.

[13] Alternatively, one could think of consumers in the model as end-users in the event that downstream competition is perfectly-competitive or monopolistically competitive so final retail price is a percentage markup above wholesale price (p). In the latter case, part of the price coefficient α would account for the fixed downstream markup.

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

to a demand shifter and α attenuates the degree to which consumers value quality versus price where higher priced goods. For simplicity I assume that $(\alpha, \xi^{\mathrm{I}})$ 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 r depends on consumer differences in these heterogenous tastes for quality:

$$A_{rt}\left(x_{\cdot}, p_{\cdot t}, ; \alpha, \xi^{\mathrm{I}}\right) = \{\epsilon_{irt} | u_{irt} \geq u_{ikt} \quad \forall k = 0, 1, \ldots, J_t\}\ , \tag{2}$$

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_{rt} analytically. I define d_{rt} as the probability that consumer i purchases product r in period t:

$$d_{rt}(p) = \frac{exp(x_r + \alpha p_{rt} + \mathbb{1}_{\{r=\mathrm{I}\}}\xi^{\mathrm{I}})}{\sum_{k \in J_t} exp(x_k + \alpha p_{kt} + \mathbb{1}_{\{k=\mathrm{I}\}}\xi^{\mathrm{I}})} \tag{3}$$

As consumers are ex ante identical, d_{rt} is also the predicted market share for a period t firm with quality x which faces competition ($i.e.$, $\sum_{k \in J_t, k \neq r} exp\left[x_k + \alpha p_{kt} + \mathbb{1}_{\{k=\mathrm{I}\}}\xi^{\mathrm{I}}\right]$). Consumer demand in terms of quantity follows immediately: $y_{rt}(p) = d_{rt}(p) \times M_t$. All else equal, a firm's demand is increasing in its product quality q, the number of consumers in the market (via M), and if it produces product in-house (provided $\xi > 0$); but decreasing price (provided $\alpha < 0$) and the number of competitors in the market.

Profits. Labor is the only input into the production process and is supplied inelastically by households.[15] 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.

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 $\mu(x, I)$ is the mass of type "I" firms with product quality x while $\mu(x, F)$ corresponds to the mass of type "F" firms with product quality x. Since consumer demand (Equation 3) is not a function of the identity of product r explicitly but

[15] 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.

rather solely on its quality (x), how it is produced (ξ), the product qualities of competing varieties μ, and upon the prices chosen by the firms (p); we can rewrite (3) to as follows:[16]

$$d_t^{\mathrm{j}}(x,p;\mu) = \frac{exp\left(x + \alpha p_t^j + \mathbb{1}_{\{j=\mathrm{I}\}}\xi^{\mathrm{I}}\right)}{\sum_{k\in\{\mathrm{I,F}\}}\sum_{x\in\mathcal{Q}}\mu_t^k(x)\times exp\left(x+\alpha p_t^k + \mathbb{1}_{\{k\in\mathrm{I}\}}\xi^{\mathrm{I}}\right)}. \tag{4}$$

The firm of type $j = \{I, F\}$ which produces product r in period t therefore chooses price $p_t^{\mathrm{j}}(x;\mu)$ to maximize static profits taking into account the product qualities ($x_{\cdot t}$), market shares $d^{\mathrm{j}}(x,p;\mu)$, and prices of the competition ($p_{\cdot t}$) satisfying the following first-order condition:

$$\begin{aligned} p_t^{\mathrm{I}}(x;\mu_t) \quad &= 1 + \underbrace{\left[\frac{\partial d_t^{\mathrm{I}}(x,p;\mu_t)}{\partial p_t^{\mathrm{I}}}\right]^{-1}\times d_t^{\mathrm{I}}(x,p;\mu_t)}_{b_t^{\mathrm{I}}(x,p;\mu_t)} \\ p_t^{\mathrm{F}}(x;\mu_t) \quad &= \lambda_t + \underbrace{\left[\frac{\partial d_t^{\mathrm{F}}(x,p;\mu_t)}{\partial p_t^{\mathrm{F}}}\right]^{-1}\times d_t^{\mathrm{F}}(x,p;\mu_t)}_{b_t^{\mathrm{F}}(x,p;\mu_t)} \end{aligned} \tag{5}$$

where period t subscripts indicate that equilibrium prices can vary across time due to changes in type "F" firm marginal cost (λ_t) and changes in the firm size distribution (μ_t). The terms $b_t^{\mathrm{j}}(x,p;\mu)$ 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.

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 $p^{\mathrm{j}\star}(x,\mu)$ $\forall \mathrm{j} \in \{\mathrm{F,I}\}$ which solves the system of equations defined by (5) (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 $s^{\mathrm{j}}(x,p;\mu)$.

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

$$\begin{aligned} \pi_t^{\mathrm{I}\star}(x;\mu_t,M_t) \quad &= \left[p_t^{\mathrm{I}\star}(x;\mu_t) - 1\right]\times d_t^{\mathrm{I}\star}\left(x,p_t^\star;\mu_t\right)\times M_t, \\ \pi_t^{\mathrm{F}\star}(x;\mu_t,M_t) \quad &= \left[p_t^{\mathrm{F}\star}(x;\mu_t) - \lambda_t\right]\times d_t^{\mathrm{F}\star}\left(x,p_t^\star;\mu_t\right)\times M_t. \end{aligned} \tag{6}$$

[16] This is a common approach to modeling consumer demand which dates back to Lancaster (1966).

3.2 Dynamic Evolution of the Industry

I turn now to the dynamic decisions faced by firms and discuss the evolution of the endogenous distribution of μ. There are two ways in which the industry firm distribution changes from one period to the next. I begin first by describing the exogenous stochastic movement of firms across quality levels. I then turn to the evolution of μ through the endogenous exit and entry of IDM and Fabless firms in response to changes in market size (M_t), entry costs ($f^{\mathrm{I}}_{e,t}, f^{\mathrm{F}}_{e,t}$), and Fabless production costs (λ_t). As with spot-market profits, I focus on pure-strategy equilibria and define $\sigma_{i,t}$ as the pure strategy exit and entry decisions of firm i and $\sigma_{-i,t}$ as the pure strategy exit and entry decisions of other firms. The inclusion of period t subscripts indicates that these strategies may vary over time.

Exogenous Incumbent Research. The product quality for firms which do not exit the industry then evolves according to the following exogenous process: A firm of product quality x increases (decreases) its quality by Δ_x with probability k^j_t $(1 - k^j_t)$. This R&D process exhibits two traits. First, this step-by-step process implies that a firm which produces a high quality product today is likely to produce a high quality product tomorrow. Second, I allow for differential research abilities between the two firm types and across time but not across firms of different product quality. The model therefore is consistent with Gilbrat's Law as in Atkeson and Burstein (2010).

Firm Value and Exit. I assume there exists an exogenous, positive, and constant-over-time world interest rate which in equilibrium pins down the discount factor $\beta \in (0, 1)$. At the beginning of each period, incumbent firms observe a private, real-valued sell-off value ϕ. After profits are realized, each firm i compares its private sell-off value with the continuation value of remaining in the industry. If the sell-off value exceeds the value of remaining in the industry, firm i chooses to exit and earns the sell-off value. Once a firm is sold, the exiting firm ceases to exist permanently and the entrepreneur which owns the firm retains no knowledge which would provide her a comparative advantage of re-entering the industry relative to other entrepreneurs. Thus, I exclude the possibility of serial entrepreneurs.[17]

An individual firm of type j $\in \{\mathrm{F}, \mathrm{I}\}$ which produces a product of quality x and faces industry state $\hat{s}_t$ solves the following recursive problem:

$$V^j_t(x_t, \phi_t; \mu_t) = \overbrace{\pi^j_t(x_t; \mu_t)}^{\text{Static Profit}} + \overbrace{\max\Big\{\phi_t,\ E\Big[V^j_{t+1}(x_{t+1}, \phi_{t+1}; \mu_{t+1}) \mid x_t, \mu_t\Big]\Big\}}^{\text{Exit}} \tag{7}$$
$$\text{s.t.} \quad \mu_{t+1} = P(\mu_t; \sigma_{i,t}, \sigma_{-i,t}), \ \underbrace{M_{t+1} = \Psi(M_t)}_{\text{Perfect Foresight}}.$$

[17] Firms are assumed to exit the industry which benefits all firms roughly the same. In practice, 79% of exiting firms are acquired by a competitor so much of the benefit of acquisition is internalized by a single firm. In a companion paper, I assess the equilibrium effects of mergers & acquisitions of firm investment and market entry.

where the continuation value of the firm is determined by the evolution of the firm's product quality and the industry state where I assume the evolution of the M is exogenous and firms have perfect foresight over this process.[18] The inclusion of period subscripts communicates the fact that I allow for variation in period t profits due to changes in the underlying costs of Fabless production which in turn affects the period t valuation of the firm.

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.[19] Upon paying the 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 $\tilde{V}_t^j(\hat{s}_t)$ as the expected discounted value of entry as a type $j \in \{\mathrm{F}, \mathrm{I}\}$ firm conditional on industry state $\hat{s}_t$ where

$$\tilde{V}_t^{\mathrm{I}}(\mu_t) = \beta \sum_{x \in \mathcal{X}} V_t^{\mathrm{I}}(x, \mu_{t+1}) dG(x) \tag{8}$$

$$\tilde{V}_t^{\mathrm{F}}(\mu_t) = \beta \sum_{x \in \mathcal{X}} V_t^{\mathrm{F}}(x, \mu_{t+1}) dG(x) \tag{9}$$

$$\text{s.t. } \mu_{t+1} = P(\mu_t; \sigma_{i,t}, \sigma_{-i,t}) \ .$$

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

$$\mathcal{E}_t^{\mathrm{I}} = \mathrm{Pr}_t^{\mathrm{I}}(\text{entry}) \times \mathcal{N} \tag{10}$$

$$\mathcal{E}_t^{\mathrm{F}} = \mathrm{Pr}_t^{\mathrm{F}}(\text{entry}) \times \mathcal{N}, \tag{11}$$

[18] Alternatively, one could test for firm beliefs consistent with the evolution of the industry as in Jeon (2019).

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

where market entry will vary over time due to variation in the expected discounted profits of entry (Equations 8 & 9).

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

$$\mu^j_{t+1}(x) = \underbrace{\Pr\big(\phi < V^j_t(x-\Delta_x, \mu_t)\big)}_{\text{Prob. Continue}} \times \Bigg[\underbrace{k^j_t \times \mu^j_t(x-\Delta_x)}_{\substack{\text{Firms successfully}\\ \text{improve quality}}}\Bigg] +$$

$$\underbrace{\Pr\big(\phi < V^j_t(x+\Delta_x, \mu_t)\big)}_{\text{Prob. Continue}} \times \Bigg[\underbrace{\big(1-k^j_t\big) \times \mu^j_t(x+\Delta_x)}_{\substack{\text{Firms unsuccessfully}\\ \text{improve quality}}}\Bigg] + \underbrace{\mathcal{E}^j_t dG(x)}_{\text{Entry}}. \tag{12}$$

3.3 Moments-based Markov Equilibrium

Thus far I have described the model as a function of the entire firm size distribution μ_t. In this section, I describe how to modify the model such that firms best respond to the competition based on a select set of sufficient moments / statistics of μ_t rather than the whole distribution itself. A *moments-based Markov equilibrium* (MME) is therefore an equilibrium of moment-based firm strategies. Define $\hat{s}_t$ as a particular set of useful moments which firms will condition their pure strategy pricing, exit, and entry decisions.

Static Firm Pricing and Profits. From 5 we observe that firms set prices by adding a markup above their marginal production costs. If we assume that firms are sufficiently small such that they do not internalize the aggregate effects of their pricing decisions as in Besanko, Perry, and Spady (1990), firm markups b^j are constant and common across quality levels as well as firm types:

$$p^{\mathrm{I}\star}_t = 1-\alpha$$
$$p^{\mathrm{F}\star}_t = \lambda_t - \alpha$$

where $\alpha < 0$ corresponds to downward-sloping demand. Given that there are hundreds of firms in the semiconductor industry, assuming monopolistic competition among the firms amounts to a good approximation of optimal price-setting in the more general Bertrand-Nash equilibrium.

Period t profits for a type-j firm of product quality x are therefore impacted by changes in the Fabless production cost λ_t, the industry moment $\hat{s}_t$, and market size M_t:

$$\begin{aligned}
\pi^{\mathrm{I}\star}_t(x;\hat{s}_t, M_t) &= \tfrac{M_t \times (p^{\mathrm{I}\star}_t - 1)\times \exp\left(x+\alpha p^{\mathrm{I}\star}_t + \xi^{\mathrm{I}}\right)}{\hat{s}_t}, \\
\pi^{\mathrm{F}\star}_t(x;\hat{s}_t, M_t) &= \tfrac{M_t \times (p^{\mathrm{F}\star}_t - \lambda_t)\times \exp\left(x+\alpha p^{\mathrm{F}\star}_t\right)}{\hat{s}_t}
\end{aligned} \tag{13}$$

where I define $\hat{s}_t$ as the industry price index:

$$\hat{s}_t = \sum_{x \in \mathcal{Q}} \exp\big(x + \alpha p_t^{\mathrm{I}\star} + \xi^{\mathrm{I}}\big)\mu_t^{\mathrm{I}}(x) + \sum_{x \in \mathcal{Q}} \exp\big(x + \alpha p_t^{\mathrm{F}\star}\big)\mu_t^{\mathrm{F}}(x) \tag{14}$$

Dynamic Firm Decisions. I now turn to re-defining the firm value function and corresponding firm decision rules based on the industry state $\hat{s}$ where firm value depends not only on the exogenous evolution of its own state but also on its *perceived* evolution of the industry state due to the endogenous exit and entry of IDM and Fabless firms. Formally, the value of type-j firm i with quality x in industry state $\hat{s}_t$ is

$$\begin{aligned} V_t^j(x_t, \phi_t; \hat{s}_t) &= \pi_t^j(x_t; \hat{s}_t) \ + \ \max\Big\{\phi_t,\ E\Big[V_{t+1}^j(x_{t+1}, \phi_{t+1}; \hat{s}_{t+1}) \mid x_t, \hat{s}_t\Big]\Big\} \\ \text{s.t.} \quad \hat{s}_{t+1} &= \hat{P}_t(\hat{s}_t; \sigma_{i,t}, \sigma_{-i,t}) \end{aligned} \tag{15}$$

where I maintain that firms have perfect foresight over the evolution of aggregate demand M_t, and the expectation is taken with respect to the *perceived* transition kernel $\hat{P}_{\sigma_{i,t},\sigma_{-i,t}}$ which specifies probabilities from moving from the current industry state $\hat{s}_t$ to future industry states $\hat{s}_{t+1}$. It is important to note that this process need not be constitute a Markov process even if the underlying state's evolution (x_t, μ_t) is a Markov process. Ifrach and Weintraub (2016) demonstrate, however, the Markov process in an equilibrium where all firms use moment-based strategies based on this transition Kernel amounts to a good approximation to the non-Markovian evolution of $(x_t, \hat{s}_t)$.

Firm entry satisfies

$$\mathcal{E}_t^{\mathrm{F}}(\hat{s}_t) = \frac{exp(\tilde{V}_t^{\mathrm{I}}(\hat{s}_t) - f_{e,t}^{\mathrm{I}})}{1 + exp(\tilde{V}_t^{\mathrm{I}}(\hat{s}_t) - f_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}}(\hat{s}_t) - f_{e,t}^{\mathrm{F}})} \times \mathcal{N} \tag{16}$$

$$\mathcal{E}_t^{\mathrm{F}}(\hat{s}_t) = \frac{exp(\tilde{V}_t^{\mathrm{F}}(\hat{s}_t) - f_{e,t}^{\mathrm{F}})}{1 + exp(\tilde{V}_t^{\mathrm{I}}(\hat{s}_t) - f_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}}(\hat{s}_t) - f_{e,t}^{\mathrm{F}})} \times \mathcal{N}, \tag{17}$$

where the dependence of these strategies upon the transition kernels is implied through the entry value functions $\big(\tilde{V}_t^{\mathrm{I}}(\hat{s}_t), \tilde{V}_t^{\mathrm{F}}(\hat{s}_t)\big)$.

Non-stationary Aspects. My objective is in this study is to assign levels of importance to various factors which could explain the rise of the Fabless business model. I therefore allow for profit functions, value functions, and firm strategies to vary across time. While this provides the flexibility to use the model to address my research question, such flexibility introduces a great deal of complexity which I address here.

I solve the model by assuming there exist two stationary MME on either side of the transition. In particular, I assume that data between 1980 and 1990 amounts to the first stationary MME and there exists a stationary MME at some point beyond 2013. The first MME provides a starting point for the initial industry state while the second stationary MME provides the period T

value function. In the first stationary MME the implicit assumption is that not only is the industry in a stationary MME but also changes in the industry (e.g., Fabless entry and production costs) which drive the transition to the second stationary MME is unexpected and therefore did not affect firm innovation decisions. For the second stationary I assume that all model primitives, including aggregate demand are fixed at those found in 2013. This does not, however, require that the values of the profit or value function are fixed so firm entry, exit, and type (IDM vs. Fabless) decisions which follow period T strategies in 2013 (for $T > 2013$) may continue to evolve to a recurrent set of values consistent with the stationary MME. For example, in the second stationary MME it could be the case that 200 to 250 firms populate the industry while the model predicts 500 firms in 2013. In the equilibrium as the industry evolves from 2013 to T and firms follow period T strategies thereafter, the equilibrium number of firms eventually reaches 250 firms and remains between 200 and 250 firms thereafter.

Solving the game in this manner amounts to solving a finite-period game as in Goettler and Gordon (2011) and Igami (2017, 2018) so generating equilibrium value functions (and hence firm strategies) along the transition path is achieved via backwards-induction. As the second stationary MME amounts to an infinite-period game, the issue of equilibrium multiplicity remains whereas there exists a unique equilibrium in the finite setting of Goettler and Gordon (2011) and Igami (2017, 2018) by assumption.

3.4 Definition of the Non-stationary Moments-Based Markov Equilibrium

A non-stationary Moments-based Markov Equilibrium (nMME) is comprised of period t entry, exit, firm-type strategies σ_t such that for a periods t:

1. The incumbent firm exit strategy solves (15).
2. Firm entry and type strategies satisfy equations (16) and (17).
3. Strategies generate period t transition kernels $\hat{P}_{\sigma_t}(\hat{s}', \hat{s})$.

Existence follows directly from the existence of MME (Ifrach and Weintraub, 2016), while uniqueness of equilibria is not guaranteed.

4 Estimation

My empirical approach to understanding the factors which explain the rise of the Fabless business model requires estimating the model from Section 3 using the data from Section **??**. In this section I describe how I estimate key model parameters, discuss identification, and present estimation results.

4.1 Preliminaries

Time periods are defined in years where $t = 1990, ..., 2013$. 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 model sell-off values are firm type-specific (IDM or Fabless) are composed of two components: a common component ($C > 0$) and a multiplicative random component which is drawn i.i.d. from exponential distribution. Thus, the probability a type-j firm of quality x chooses remain in the industry is

$$\Pr^j\big(\phi C < EV^j_{t+1}(x_{t+1}, \hat{s}_{t+1})\big) = 1 - exp\big(-\eta^j \times EV^j_{t+1}(x_{t+1}, \hat{s}_{t+1})/C\big)$$

I found it helpful to set the common component $C > 0$ equal to $M_{t=1990}$ in order to keep exit rates well-behaved throughout the nMME solution algorithm. Allowing for the random draws to vary by firm type (*i.e.*, η^j) provides for the possibility that the sell-off values across IDM and Fabless firms are different. For instance, an IDM is composed of valuable tangible assets while Fabless firms are largely intangible assets (e.g., chip designs, customer contacts) so it is reasonable to suspect that, to the extent tangible assets are indeed valuable, two firms of equal quality but different business types will receive different offers to sell.

I use the long-term average return of 5% for US Treasury Bonds to pin-down β. 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. Moreover, differences in firm quality are revealed in the data via differences in firm revenue. The exogenous changes in quality k^j_t, therefore, correspond to the probability that period t IDM and Fabless firms increases their revenue state from one year to the next. For example, 65% of IDMs and 64% of Fabless firms increased their revenues between 1994 and 1995. The grid for product quality contains 100 states which ensures that the boundaries never impact the firm size distribution. For the industry state vector, I consider a state space consisting of 500 points. Given the fact that this vector must hold the recurrent industry states for both stationary MME as well as the transition path, I found it necessary to make this space vector large which also increases the computational burden of solving for the firm decision rules, particularly the firm value function required to solve for equilibrium exit strategies.

Transition Kernel for the Industry State. Firm value functions, and therefore strategies, require each firm i to accurately forecast industry state transitions via the transition kernel $\hat{P}_{\sigma_{i,t},\sigma_{-i,t}}$. Fundamentally, this comes down to taking a stand on how firms form beliefs about the future. My intent here is not to identify the best model of learning and belief formation consistent with an industry as in Dickstein and Morales (2018) and Jeon (2019). I instead assume that firms are able to solve the dynamic game and construct these transition kernels explicitly given the equilibrium behavior of firms in the industry. For the first stationary MME equilibrium, this amounts to assuming that period transitions amount to long-term observed transitions between aggregate industry states. Thus, the manager firm i "knows" $\hat{P}_{\sigma_{i,t},\sigma_{-i,t}}$ from experience. This is a similar notion as the *Experience Based Equilibrium* of Fershtman and Pakes (2012). Formally, I construct the transition kernel in the first stationary MME by simulating transitions between industry states using the observed visits to each industry state:

$$\hat{P}_{\sigma_{i,t},\sigma_{-i,t}}\left(\hat{s}', \hat{s}\right) = \limsup_{T\to\infty} \frac{\sum_{t=1}^{T} \mathbb{1}\{\hat{s}' = \hat{s}_{t+1}, \hat{s} = \hat{s}_t\}}{\mathbb{1}\{\hat{s} = \hat{s}_t\}} \tag{18}$$

Transition kernel 18 is defined only for industry states actually visited while firm strategies exist on the entire support of potential industry states. For industry states outside this recurrent set, I assume the industry state remains constant from period t to period t.[20] I also utilize (18) to construct the transition kernel for the second stationary MME as well as the transition between stationary MME. This approach is valid so long as period t firms follow the above solution algorithm to construct the equilibrium transition Kernel. In all cases, the assumption is that all firms are sufficiently small that they fail to account for the effect of their own actions (*i.e.*, entry, firm-type, or exit) on the evolution of the industry state.

4.2 A Simulated Minimum Distance Estimator

Estimating the model requires identification of the remaining parameters which I define as $\theta = \{\alpha, \xi, \lambda_t, M_t, f^{\mathrm{I}}_{e,t}, f^{\mathrm{F}}_{e,t}\}$. 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

[20] This is an arbitrary assumption which is difficult to test empirically. Ifrach and Weintraub (2016) refer to this assumption as the firms having "status quo" perceptions and investigate equilibrium effects of perturbations of this assumption.

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

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \left[g_{S,T}(\theta) - g_T^d\right]' A \left[g_{S,T}(\theta) - g_T^d\right] \tag{19}$$

subject to

$$\underbrace{\mathrm{TR}_t^d}_{\substack{\text{Total Revenue} \\ \text{in Data}}} = \underbrace{\sum_{j \in \{\mathrm{I,F}\}} \sum_{x \in \mathcal{Q}} \mu_t^j(x) p_t^j(x,\mu) d_t^j(x,\mu) M_t}_{\substack{\text{Total Revenue Predicted} \\ \text{by the Model Conditional on } \theta, M, N}}$$

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.[21] Equation (19) therefore places more weight on moments which provide better identification of θ. To increase the probability of finding a global minimum to (19), I employed a state-of-the-art minimization software (KNITRO) and repeated the minimization from different initial guesses for θ.[22] 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 nMME for each parameter guess θ. The non-stationary aspect of the equilibrium complicates analysis as it requires solving for the set of period $t = 1, ..., T$ profit functions, value functions, exit strategies, and entry strategies which comprise the equilibrium given θ. As noted above, I solve the nMME by (1) solving the first MME, (2) solving the second MME, and (3) using the period $T > 2013$ value functions to work backwards along the transition path thereby solving for equilibrium period t decision rules between the stationary MME consistent with the implied period

[21] 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.

[22] 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.

t transition kernels. I update all transition kernels by simulating the evolution of the industry state $1,000$ times.

Identification. Identification of θ derives from the role each parameter plays in the model. Identification of M_t is via total market share via the constraint in (19). Define the following operator which connects predicted market size (*i.e.*, total revenue) and observed market size:

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

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 (19) is satisfied by construction.[23]

Identification of the entry costs $(f_{e,t}^{\mathrm{I}}, f_{e,t}^{\mathrm{F}})$ comes via the entry of firms by business type $\mathcal{E}_t^{\mathrm{I}}, \mathcal{E}_t^{\mathrm{F}}$ relative to the expected value of entry: $\tilde{V}_t^{\mathrm{I}}, \tilde{V}_t^{\mathrm{F}}$. I therefore identify $(f_{e,t}^{\mathrm{I}}, f_{e,t}^{\mathrm{F}})$ by comparing the expected period t predicted by the model with the levels observed in the data. This yields 48 moments to identify the 48 parameters of $(f_{e,t}^{\mathrm{I}}, f_{e,t}^{\mathrm{F}})$.

The exit parameters $(\eta^{\mathrm{I}}, \eta^{\mathrm{F}})$ modulate the exit rates of firms. I assume these are constant across the sample (variation in sell-off values comes from variation in market size via M_t). Given that entry costs pin-down the number of entrants of each firm type, I identify $(\eta^{\mathrm{I}}, \eta^{\mathrm{F}})$ by targeting the number of IDM and Fabless firms in 2013. As noted earlier, this value may not be the equilibrium number of firms in the second stationary MME but instead by merely be the number of firms in a particular year (2013) along a much larger transition path as the industry moves to the second stationary equilibrium.

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.

[23] 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 19 to this contraction operator.

By a similar argument, Fabless marginal cost parameters $\{\lambda_t\}$ are identified using the differences in the gross margin of IDM and Fabless firms (since marginal cost of IDMs is normalized to one) where we recall that Fabless firms on average have higher margins (Table IV). Thus,

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

whenever $\lambda_t < 1$ provided p_t^{I} and p_t^{F} are not too different. Thus, α and λ_t are identified in the data by average gross margins across period t firms. Since α is constant throughout the sample, its identification is based on the average IDM margin in the sample whereas variation changes in Fabless margins across periods identifies λ_t. This yields 48 moments to identify α, λ_t (25 parameters).

The IDM demand shifter (ξ^{I}) is identified by the ratio of the enterprise value of IDM and Fabless firms where "enterprise value" is the actuarial equivalent of the firm value functions in the model. Specifically, "enterprise value" is defined as market value of common stock + market value of preferred equity + market value of debt + minority interest - cash and investments. Modulation of ξ^{I} therefore changes the relative value of IDM and Fabless firms; *i.e.*, the ratio of $V_t^{\mathrm{F}}(x, \hat{s})$ to $V_t^{\mathrm{I}}(x, \hat{s})$ decreases as $\xi^{\mathrm{I}}\uparrow$. This yields 24 moments to identify ξ^{I}.

4.3 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 2. 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.

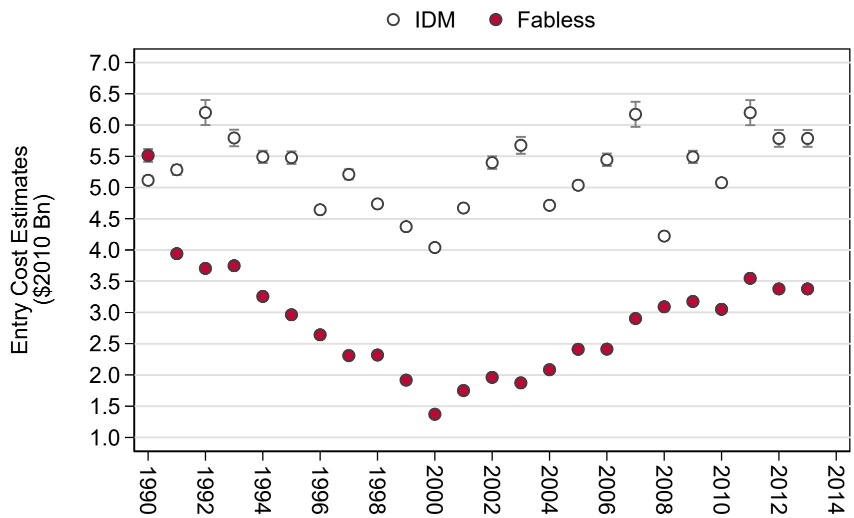
Table V: Estimation Results

Parameter	Value	S.E.	Identifying Moments (L)	Data	Model
Price Coefficient (α)	-1.5458	(0.0162)	Gross Margin (24)	0.4535	0.4490
IDM Demand Shifter (ξ^{I})	2.1500	(0.0356)	$\frac{\text{Avg. EV (Fabless)}}{\text{Avg. EV (IDM)}}$ (24)	0.3176	0.3202
IDM sell-off (η^{I})	0.0800	(0.0016)	Number of 2013 IDM Firms (1)	273	248.3954
Fabless sell-off (η^{F})	0.0149	(0.0004)	Number of 2013 Fabless Firms (1)	1,010	1,113.3413

Notes: Statistics for identifying moments correspond to the average over the periods in the sample. Number of identifying moments in parentheses.

In Figure 4, 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

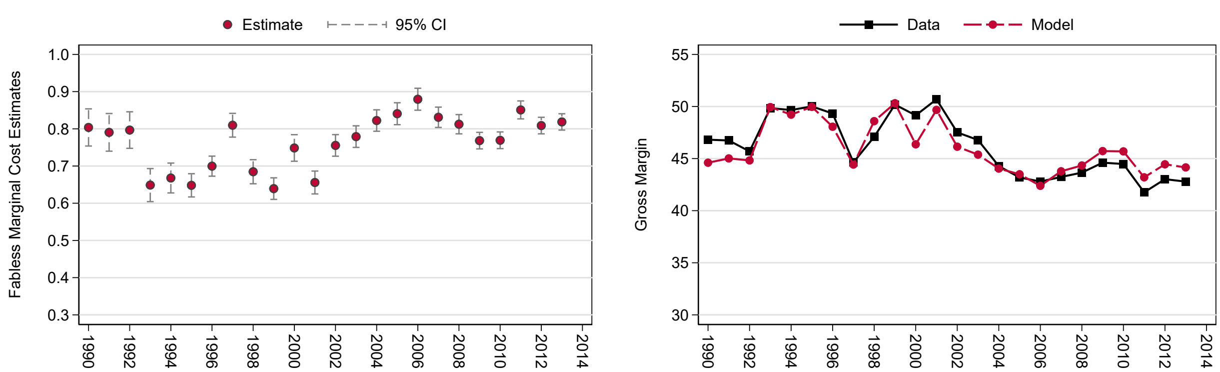
Figure 4: Estimated Entry Costs: $\hat{f}^{\mathbf{I}}_{e,t}, \hat{f}^{\mathbf{F}}_{e,t}$



Notes: Points correspond to the estimated entry costs implied by free-entry conditions (16, 17). Bars correspond to the 95/5 confidence interval.

the IDM demand shifter $\hat{\xi}^{\mathrm{I}}$ via the entry equations (16, 17). 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 5: Model Fit: Fabless Gross Margin



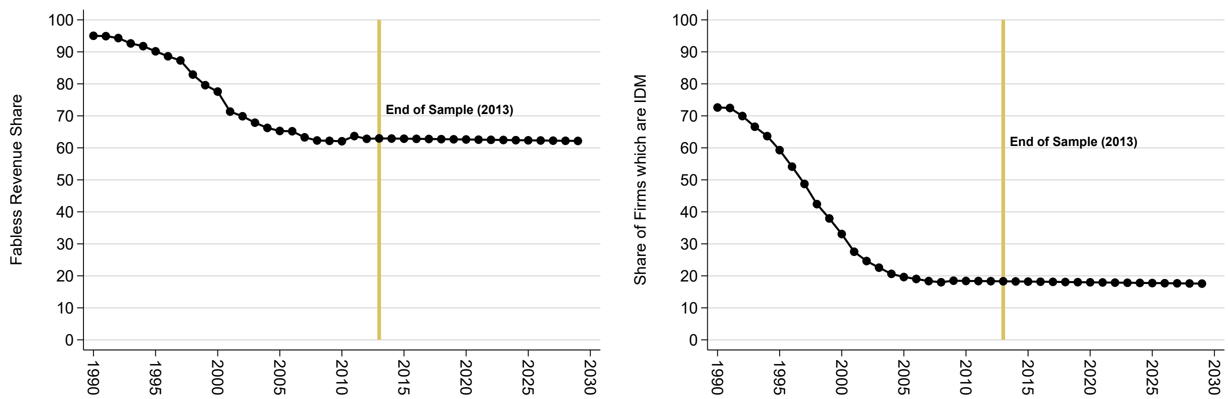
(a) Fabless MC $\{\hat{\lambda}_t\}$ (b) Fabless Gross Margin

In Figure 5 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.

4.4 Is Outsourcing the Dominant Long-run Strategy?

Igami (2018) documents that off-shoring in the hard-disk drive industry became necessary for incumbents to survive. The estimated model here, however, indicates that while Fabless firms face lower upfront and on-going costs, operating an in-house fabrication facility enables IDMs to deliver "higher quality" products. This suggests that the long-run stationary equilibrium could be segmented where Fabless and IDM firms sell to different sets of consumers. I test this hypothesis in Figure 6 where I present the long-run stationary MME implied by the estimated model.

Figure 6: A Growing and Changing Market



(a) Revenue Share (b) Composition of Firms

Notes: In panel (a) I document the estimated Fabless revenue share over the sample. In panel (b) I document the changing composition of firms.

From Figure 6 we observe that in the long-run equilibrium IDM firms account for only about 20% of all firms (panel b) but they generate 60% of industry sales. Thus, product differentiation enables this industry to support both business models in the long-run equilibrium.

5 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:

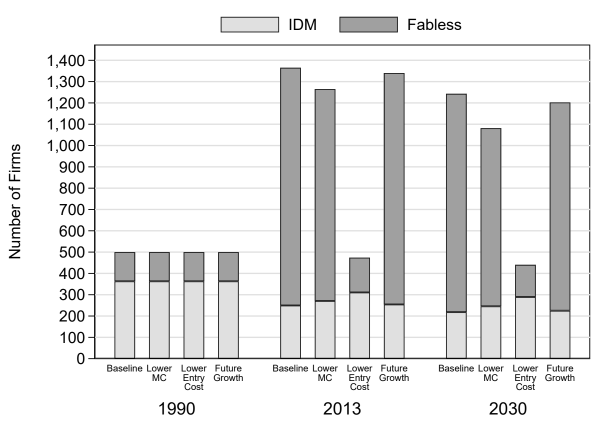
$$\mathrm{Pr}_t^{\mathrm{I}}(\mathrm{entry}) = \frac{exp(\tilde{V}_t^{\mathrm{I}} - \hat{f}_{e,t}^{\mathrm{I}})}{1 + exp(\tilde{V}_t^{\mathrm{I}} - \hat{f}_{e,t}^{\mathrm{I}}) + exp(\tilde{V}_t^{\mathrm{F}} - \hat{f}_{e,t}^{\mathrm{F}})}$$
$$\mathrm{Pr}_t^{\mathrm{F}}(\mathrm{entry}) = \frac{exp(\tilde{V}_t^{\mathrm{F}}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

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.

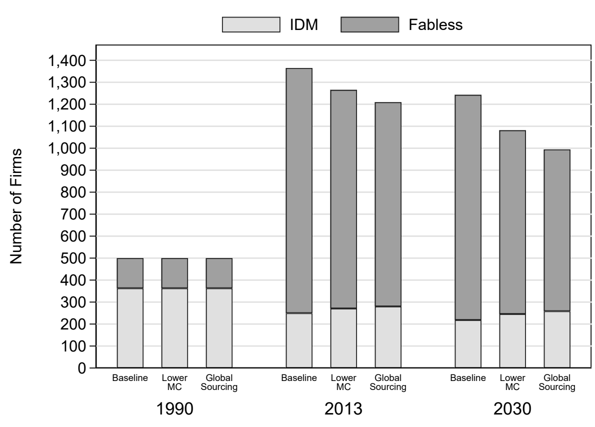
In Figure 7 I evaluate the extent to which differences in entry and production costs can explain the growth in outsourcing. In panel (a) I compare the firm composition across two scenarios. First, I equalize production costs by setting $\lambda_t = 1\ \forall t$ but I leave entry costs at their estimated levels ("MC"). Second, I equalize entry costs by increasing the period t Fabless entry cost to the estimated IDM entry cost $\hat{f}^{\mathrm{F}}_{e,t} = \hat{f}^{\mathrm{I}}_{e,t}\ \forall t$ 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.

Figure 7: Measuring the Drivers of Outsourcing



(a) Production vs Upfront Costs vs Growth



(b) Global Supply Chain

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 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.

5.1 Measuring the Impact of Venture Capital

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 8 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 can be decomposed into a principal amount required to start a IDM or Fabless firm and a "Financing Charge":

$$\hat{f}^{\mathrm{j}}_{e,t} = f^{\mathrm{j}}_{e,t} \times (1 + \text{"Financing Charge"}) \ ,$$

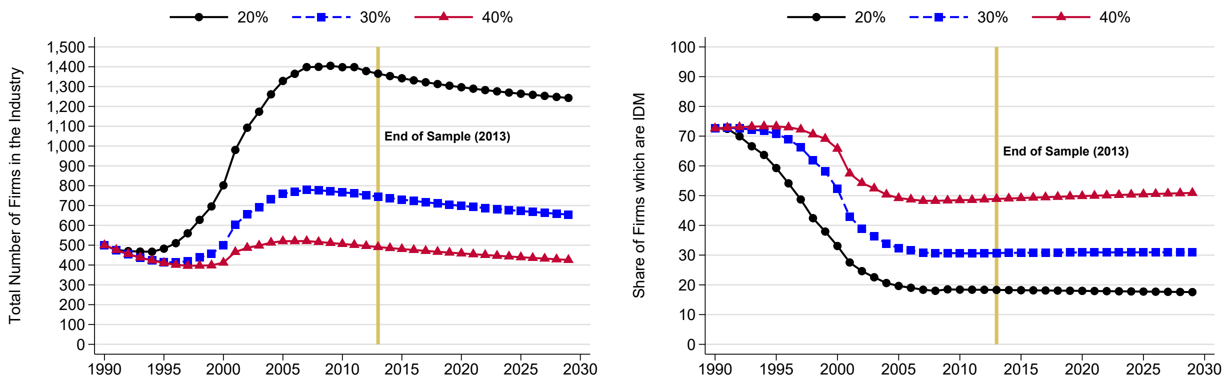
where the left-hand side is the estimated entry cost incurred by period t IDM or Fabless firms. The "Financing Charge" is simply a markup required to secure financing though it may also reflect any additional costs required to find funding.

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 – a rate of return consistent with venture capital benchmarks. I then simulate an increase in the entry costs of firms (both IDM and Fabless) by increasing the interest rate to 30% and 40% 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 (panel b). Interestingly, at financing costs the growth of Fabless firms, as a percent of total, is

[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 8: The Role of Venture Capital Funding



(a) Number of Firms (b) IDM Share

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.

6 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 entry.

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), endogenous research effort, and accounting for mergers are all promising avenues for future research.

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A Other Results

Figure 9: A Growing Market ($\hat{M}_t$)

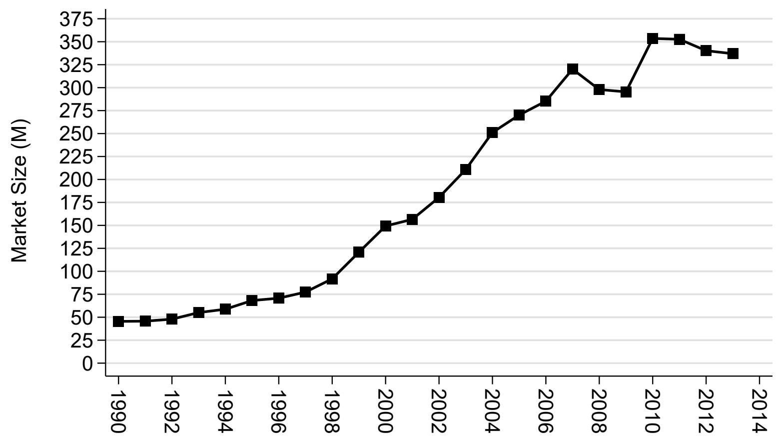

Table VI: The Foundry Market

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.