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Does the asset-light business model create value? A panel data stochastic frontier approach for the global semiconductor industry

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Abstract

This paper applies a panel data stochastic frontier approach to investigate the impacts of different business models in operating efficiencies in the global semiconductor industry. The efficiency scores are linked with the financial ratios and specified by cumulative probit distribution function, cumulative logit distribution function, and the Gumbel function respectively after disentangling the heterogeneity by the within transformation. The estimates by the nonlinear least squares technique indicate that the asset-light fabless companies have relatively higher efficiency scores among the different operating models in the global semiconductor industry.

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1 Introduction

Semiconductors, also referred to as integrated circuits (ICs) or chips, are crucial elements in the manufacturing of electronics over the last 70 years since the invention of transistors at Bell laboratories in 1947. The semiconductor industry is a driving force in the digital economy and is closely linked to many cutting-edge technologies such as advanced wireless networks, artificial intelligence, and quantum computing. During the early years of the semiconductor industry, it almost entirely involves the integrated device manufacturer (IDM) business model, that one company handles all of the production stages in-house, including research and design (R&D), front-end wafer fabrication, and back-end assembly and test (A&T). A well-known IDM is the microprocessor manufacturer Intel, which nowadays has six wafer fabrication sites, three A&T manufacturing locations, and more than one hundred thousand employees worldwide. Due to the steadily increasing complexity of the leading-edge ICs characterized by Moore's law (e.g., see Flamm 2017), the enormous capital expenditure (CAPEX) accompanying with proportionally increasing R&D and labor costs imposes a heavy burden even for the largest IDMs, which underlays the birth of the fabless-foundry business model in the semiconductor industry in the 1980s.

In the fabless-foundry business model, the fabless firms focus on the design and sales of chips and partner with pure-play foundries for front-end wafer fabrication as well as a third group of companies for back-end outsourced semiconductor assembly and test (OSAT). Vertical disintegration by the fabless-foundry model drastically reduces the burden of CAPEX in the semiconductor industry and brings up the prosper and flourish of the asset-light fabless firms with diversified products for various applications (e.g., see Sarma and Sun 2017). The fabless companies, such as Qualcomm and Nvidia, direct all their resources in designing state-of-the-art chips and contract out both front-end wafer fabrication and back-end A&T so that they are risk-free in the setting up, maintaining, and upgrading of the profoundly expensive fabrication facilities. In contrast, the IDMs derive efficiency from vertical integration. In the development of bleeding-edge ICs which requires close coordination between product design and process verification, IDMs achieve performance advantages when technological developments involve complex problems and gain efficiency by the internalization of transaction costs (e.g., see Dibiaggio 2007, and Kapoor and Adner 2012). Hence whether the vertical integrated IDM model or the vertical specialized fabless-foundry model operates more efficiently is an empirical question in the global semiconductor industry.

Strategic management approach suggests that intra-industry performance differences can be attributed to sustainable competitive advantage (e.g., see Barney 1991, and Mahoney 1995). The resource-based view of competitive advantage specifies that resources are important antecedents to a firm's overall performance as well as sources of sustained competitive heterogeneity among firms (e.g., see Barney 2001). Liou et al. (2008) and Tang and Liou (2010) suggest extending the causal relationship between competitive advantage and superior performance to a strategy-configuration performance causal series. They apply this theoretical framework to the global semiconductor industry and argue that the presence of competitive advantage of the asset-light business model can be reflected in the causal relationship between resource configuration, dynamic capability, and observable financial performance. However, though the terms competitive advantage and performance are often used interchangeably, the two constructs are acknowledged to be conceptually distinct (e.g., see Powell 2001, and Newbert 2008). Furthermore, the debate on a conceptually clear and unambiguous definition of competitive advantage is far from over (e.g., see O'Shannassy 2008, and Sigalas et al. 2013).

Production frontier is another econometric approach for performance evaluation. There are rich records of efficiency estimation by production frontier in the semiconductor industry, most of which follow the data envelopment analysis (DEA) method. For example, Chu et al. (2008) use the DEA technique to measure the relative performance for global leading fabless firms, while Lu et al. (2013) and Lin et al. (2019) use the DEA model to study the semiconductor industry in the US and Taiwan respectively. Despite its flexible functional form, a main drawback of the DEA approach is the ignoring of statistical noise and accounting for all deviations from the frontier to inefficiency. In contrast, the stochastic frontier analysis (SFA) approach has the attraction of naturally including an error term in the econometric regression framework, but it also has the disadvantage of requiring ex-ante functional form for both the frontier and the inefficiency term. For instance, Kumbhakar et al. (2012) apply the SFA framework to investigate the impact of R&D activities on firm performance, but their approach mixes up firms from different industries, which hardly seems to correspond to the assumption of a consistent production function.

This paper plans to merge the advantages of both the strategic management approach and the SFA approach to investigate the impact of business model on firm-level operating efficiency in the global semiconductor industry. The panel data SFA model by Paul and Shankar (2018, 2020) is chosen for the following reasons. First, this model specifies the efficiency effects by a cumulative distribution function which eschews both the restriction of a one-sided inefficiency term and the transformation to limit the inefficiency scores in a unit interval. Hence efficiency effects can be measured by financial ratios as suggested by Tang and Liou (2010). Second, the unobserved heterogeneities are within-transformed so that it is able to estimate the firm level efficiency scores under the production frontier for the highly globalized semiconductor industry. Third, it is a one-step approach that the frontier function and the efficiency effects are estimated simultaneously, keeping away from the measurement errors by a two-step procedure (e.g., see Schmidt 2011).

The paper is organized as follows. Section 2 introduces the methodology for this study. Section 3 describes the data and defines the variables used for the estimation. Section 4 presents the empirical results of the impact of business model on performance assessment in the semiconductor industry. The last section concludes.

2 The methodology

Efficiency and productivity are core concepts of economics. The SFA approach introduced by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and Broeck (1977) has an appealing feature of allowing for both a one-sided inefficiency term and a two-sided statistical noise term. Schmidt and Sickles (1984), Battese and Coelli (1988), etc., extend the SFA framework to panel data with a time-invariant inefficiency term.

Cornwell et al. (1990), Battese and Coelli (1992), etc., introduce models with a time-varying inefficiency term in panel data. Greene (2005) argues that these approaches treat unobserved heterogeneity as a measure of inefficiency and proposes a true fixed effects model which distinguishes between time-invariant unit-specific heterogeneity and time-varying inefficiency. However, Greene (2005) uses dummy variables to represent heterogeneity which encounters the incidental parameters problem. Wang and Ho (2010), Chen et al. (2014), Belotti and Ilardi (2018), etc., apply various maximum likelihood approaches to estimate Greene's model, all of which need extra transformation to restrict the inefficiency scores in a unit interval.

Some studies have used a two-step approach, where efficiency scores are estimated in the first step, and the estimates of the efficiency scores are regressed against a set of exogenous variables which are hypothesized to influence a firm's inefficiency in the second step. It is known that the inconsistent assumptions of the inefficiency term between the two steps generates biased estimation in such a two-step approach so that the mainstream of SFA proposes to estimate the efficiency scores and efficiency effects by a one-step procedure (e.g., see Kumbhakar et al. 1991). Battese and Coelli (1995), Kumbhakar and Wang (2005), Alvarez et al. (2006), etc., adopt different techniques to extend the one-step procedure to panel data. Recently, Parmeter et al. (2017) propose a nonparametric approach to estimate the distribution free inefficiency effects which needs additional constraints, such as the method of Du et al. (2013), to get nonnegative estimates of the inefficiency term. Paul and Shankar (2018, 2020) propose a distribution-free efficiency effect model which uses a cumulative distribution function to specify the efficiency effects and eschews the assumption of one-sided inefficiency term.

The Paul and Shankar (2020) model is an extension of Paul and Shankar (2018) which accounts for time-invariant unobserved heterogeneity and can be expressed as

$$Y_{it} = \exp\left(\alpha_i + x_{it}\beta + v_{it} + \frac{1}{\mu}\ln[H(z_{it}\gamma)]u_{it}\right), \tag{2.1}$$

where $i = 1, ..., N$ denotes each of the individual firms, $t = 1, ..., T_i$ denotes the observed time period of each i, α_i is the firm-specific fixed effect, v_{it} represents the random noise, and $\frac{1}{\mu}\ln[H(z_{it}\gamma)u_{it}]$ is a one-sided inefficiency term with the restriction that $0 \leq H(z_{it}\gamma) \leq 1$, and $\mu = E(u_{it})$. The equation (2.1) can be written in a logarithmic form as

$$y_{it} = \alpha_i + x_{it}\beta + \ln[H(z_{it}\gamma)] + \varepsilon_{it}, \tag{2.2}$$

where $y_{it} = \ln(Y_{it})$, and $\varepsilon_{it} = v_{it} + \frac{1}{\mu}\ln[H(z_{it}\gamma)](u_{it} - \mu)$. After the within transformation to eliminate the unobserved influence of α_i, we can simplify (2.2) as

$$\widetilde{y}_{it} = \widetilde{x}_{it}\beta + \ln\left(\frac{H(z_{it}\gamma)}{\left(\prod_{p=1}^{T_i} H(z_{ip}\gamma)\right)^{\frac{1}{T_i}}}\right) + \widetilde{\varepsilon}_{it} \tag{2.3}$$

where $\widetilde{w}_{it} = w_{it} - \frac{1}{T_i}\sum_{p=1}^{T_i} w_{ip}$ for $w \in \{y, x, \varepsilon\}$. Equation (2.3) can be estimated by the nonlinear least squares (NLS) estimator which minimizes the sum of squared errors

$$\arg\min_{\beta,\gamma} \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(\widetilde{y}_{it} - \widetilde{x}_{it}\beta - \ln\left(\frac{H(z_{it}\gamma)}{\left(\prod_{p=1}^{T_i} H(z_{ip}\gamma)\right)^{\frac{1}{T_i}}}\right)\right)^2 \tag{2.4}$$

with respect to parameters β and γ. Paul and Shankar (2020) prove the consistency of the NLS estimator in (2.4) and propose to estimate the variance of the random noise v_{it} by

$$\widehat{\sigma_v}^2 = \frac{1}{L-K}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(\widehat{\varepsilon_{it}}^2 - \frac{[\ln(H(z_{it})\widehat{\gamma})]^2}{\widehat{\mu\delta}}\right) \tag{2.5}$$

where $\widehat{\mu\delta} = \sqrt{\frac{2\sum_{i=1}^{N}\sum_{t=1}^{T_i}[\ln(H(z_{it}\widehat{\gamma}))]^6}{\sum_{i=1}^{N}\sum_{t=1}^{T_i}[\widehat{\varepsilon_{it}}\ln(H(z_{it}\widehat{\gamma}))]^3}}$, $L = \sum_{i=1}^{N} T_i$, and K is the total number of parameters β and γ.

Once the coefficient vectors β and γ are estimated, the individual fixed effects α_i can be retrieved as

$$\widehat{\alpha}_i = \frac{1}{T_i}\sum_{t=1}^{T_i}\left(y_{it} - x_{it}\widehat{\beta} - \ln(H(z_{it}\widehat{\gamma}))\right) \tag{2.6}$$

and the mean technical efficiency can be derived directly as

$$\widehat{TE_{it}} = \exp\left(\ln[H(z_{it}\widehat{\gamma})]\right) = H(z_{it}\widehat{\gamma}), \tag{2.7}$$

which avoids the transformation to calculate the efficiency scores. The selection of the function $H(z_{it}\gamma)$ is flexible, with the only restriction that $H(z_{it})$ is in a unit interval. A cumulative distribution function such as $\Phi(z_{it}\gamma)$ or any function constrained to lie between 0 and 1, such as the Gumbel function of the form $G(z_{it}\gamma) = e^{-e^{-z_{it}\gamma}}$, would be suitable for $H(z_{it})$. Another feature of using $H(z_{it}\gamma)$ to represent the technical efficiency is that it eschews the widely used assumption of a one-sided distribution of the inefficiency term in almost all the existing SFA models. Hence, it is convenient to bridge the efficiency measure $H(z_{it})$ to the operating performance, such as the financial ratios in Liou et al. (2008) and Tang and Liou (2010).

3 Data and Variable Specification

The data are collected from the sub-industry of semiconductors in Compustat database over the period of 20 years 1999–2018. Since the semiconductor industry is highly globalized, I combine data from both the Compustat North America database and the Compustat Global database to cover companies in the whole industry. I exclude photovoltaic producers, liquid crystal display manufacturers, and light-emitting diode manufacturers from the dataset, limiting the sample to only IC manufactures. Under such restriction, the sample includes 5136 observations from 470 unique companies in 1999–2018. Table 1 breaks down the sample by four kinds of business models, including fabless, IDM, foundry, and OSAT, which can naturally be grouped into three categories by the intensity of labor and capital. The first category contains fabless companies that are asset-light but labor-intensive for chip design. Over half of the companies in the semiconductor industry are in the fabless model since the barriers to entry are much lower for the asset-light fabless companies than for the asset-heavy manufacturers. The second category contains foundries and OSATs, both of which focus on fabrication and depend heavily on CAPEX for the capital-intensive facility construction and equipment maintenance. The third category contains IDMs which are both labor-intensive and capital-intensive because IDMs carry out all stages of production in-house.

Table 1: Number of observations by business model

Year	All	Fabless	IDM	Foundry	OSAT
1999	125	68	38	10	9
2000	149	81	43	10	15
2001	155	83	46	10	16
2002	213	121	48	17	27
2003	241	143	49	19	30
2004	264	159	54	21	30
2005	260	162	54	17	27
2006	267	161	56	20	30
2007	269	163	52	21	33
2008	278	172	51	20	35
2009	290	180	53	21	36
2010	300	180	59	23	38
2011	298	177	60	22	39
2012	301	180	61	22	38
2013	313	183	65	24	41
2014	302	172	62	25	43
2015	288	163	59	24	42
2016	283	162	54	23	44
2017	275	156	51	23	45
2018	265	151	48	22	44
TOTAL	5,136	3,017	1,063	394	662
No. Unique Firms	470	288	83	36	63

Identifying the inputs and outputs has always been a subject of controversy in the estimation of production frontier, without exception in the semiconductor industry. Hence I sort the most commonly used variables in the empirical papers which apply the production frontier approach for performance evaluation in the semiconductor industry and specify one output (revenue (Y)) and three inputs (labor, measured by the number of employees (X_1); cost of goods sold (X_2); and capital investment, measured by property, plant, and equipment (PP&E) (X_3)) for the production function. For the efficiency term, I follow the theory of competitive advantage, especially in case of the asset-light business model (e.g., see Liou et al., 2008 and Tang and Liou, 2010), to specify two financial ratio variables (fixed asset turnover ratio, measured by the revenue of a company divided by the value of its fixed assets (Z_1); and R&D expense to revenue ratio, measured by the percentage of sales that is allocated to R&D expenditures

(Z_2)). As there are more than one hundred financial ratios in common use, Liou et al. (2008) and Tang and Liou (2010) apply a principal component analysis to identify three key factors and find that the fixed asset turnover ratio Z_1 is a key indicator of the capital management ability of a company while the R&D expense to revenue ratio Z_2 is a dedicated indicator of the knowledge management in the semiconductor industry. The other financial indicators, either overlapped or duplicated with Z_1 or Z_2, or related to the customer and supplier relationship factor, are not selected as efficiency variables in this paper. Another advantage of using the financial ratios Z_1 and Z_2 is the scale-invariant feature which matches well with the dimensionless efficiency scores. Table 2 gives summary statistics of the variables in 1999–2018 pooled data split by the business models. The values of X_1–X_3 and Y in Table 2 are in the form before the log transformation and adjusted to the 2018 US dollar by GDP deflator to set up a criterion for comparing data across different years. The distributions of Z_1 and Z_2 are skewed to the right extremely for the fabless firms, which are consistent with the asset-light feature of the fabless model in the semiconductor industry.

Table 2: Descriptive statistics

	Min	Q1	Median	Mean	Q3	Max
			Fabless			
X_1	1	113	248	803	590	35,400
X_2	1	15,465	52,182	218,222	147,582	10,210,237
X_3	5	2,748	9,412	69,806	29,689	5,627,962
Y	3	32,198	100,203	460,156	280,885	28,365,696
Z_1	0.009	4.772	9.951	27.039	21.186	1473.976
Z_2	0.000	0.118	0.191	1.084	0.305	663.200
			IDM			
X_1	28	780	2,900	8,525	8,400	107,600
X_2	49	108,201	363,525	1,230,517	1,102,348	18,226,000
X_3	298	53,482	222,571	1,524,168	917,191	48,976,000
Y	2,679	184,205	741,897	2,932,830	2,250,155	70,848,000
Z_1	0.084	1.704	2.629	5.018	4.120	203.801
Z_2	0.000	0.058	0.120	0.132	0.181	1.663
			Foundry & OSAT			
X_1	19	439	1,577	4,114	3,931	93,891
X_2	1,123	44,567	143,472	449,317	419,758	8,841,157
X_3	88	44,868	167,886	961,037	615,005	36,542,569
Y	1,840	71,401	226,760	908,505	671,050	33,696,798
Z_1	0.039	0.794	1.218	6.792	1.924	1,789.268
Z_2	0.000	0.018	0.036	0.053	0.062	0.985

NOTE. The unit of X_1 is the number of employees.
The units of X_2, X_3 and Y are thousands US$.
All the values of X_2, X_3 and Y are adjusted to the 2018 US$ by GDP deflator.

4 Estimation Results

Estimation of the model in (2.2) is straightforward by NLS after removing the individual fixed effects by the within transformation in (2.3). Table 3 presents the estimates of the parameters in (2.4) with three kinds of different functions for $H(z_{it}\gamma)$, including the probit cumulative distribution function, the logit cumulative distribution function, and the Gumbel function, to compare the impact of the functional form for the efficiency term $H(z_{it}\gamma)$. The estimates of output elasticities, which are represented by the coefficients of inputs in the translog production function, are positive and statistically significant and do not vary much among the three models with different forms of $H(z_{it}\gamma)$. In terms of the magnitude of elasticity, capital investment which is represented by PP&E turns out to be a more important factor of production than labor. It is consistent with the fact that the semiconductor industry is capital-intensive more than labor-intensive by and large. In terms of the efficiency term $H(z_{it}\gamma)$, the positive sign of γ_1 implies that the higher the asset turnover ratio, the more efficient a company is at generating revenue from its assets. Similarly, the negative sign of γ_2 indicates that the efficiency of a firm decreases with the level up of R&D expenditure, implying that the severe competition and the continuous iteration of technology in the semiconductor industry make the heavily R&D spending a risky investment. Both the positive sign of γ_1 and the negative sign of γ_2 are consistent with the works of Liou (2011), Tsai et al. (2017), etc.

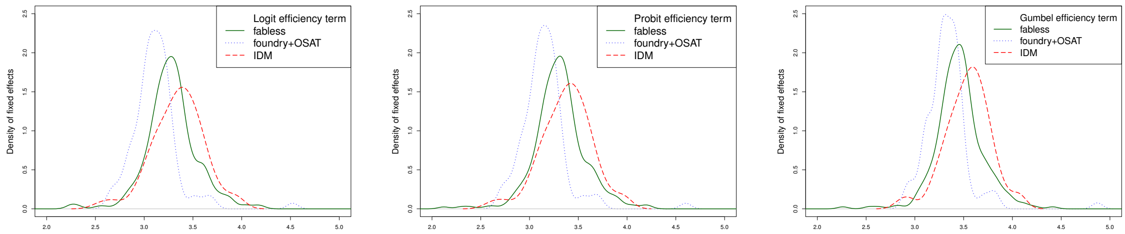
Table 3: Estimated stochastic frontiers and technical efficiency effects

	Efficiency Term — Logit —		Efficiency Term — Probit —		Efficiency Term — Gumbel —	
	Coef	SD	Coef	SD	Coef	SD
Frontier Function						
β_1	0.155^{***}	0.009	0.150^{***}	0.009	0.136^{***}	0.008
β_2	0.404^{***}	0.007	0.391^{***}	0.007	0.348^{***}	0.007
β_3	0.398^{***}	0.008	0.418^{***}	0.008	0.482^{***}	0.008
Efficiency effects						
γ_0	-1.469^{***}	0.035	-0.961^{***}	0.021	-0.785^{***}	0.016
γ_1	0.147^{***}	0.003	0.090^{***}	0.002	0.087^{***}	0.002
γ_2	-0.006^{***}	0.000	-0.002^{***}	0.000	-0.001^{***}	0.000
Wald stat.	$3,509^{***}$		$4,396^{***}$		$6,494^{***}$	
$\widehat{\sigma_v}^2$	0.403		0.426		0.600	
N	5,135		5,135		5,135	

NOTE. The null hypothesis in the Wald test is $\gamma_0 = \gamma_1 = \gamma_2 = 0$.

Figure 1 plots the distribution of individual fixed effects derived by (2.6). The heterogeneities among the business models are distinct and consistent in each form of $H(z_{it}\gamma)$. Figure 2 shows the distribution of the efficiency scores calculated by (2.7). The efficiency scores of the asset-light fabless companies have a relatively smoother distribution, while the efficiency scores of the capital intensive IDMs, foundries, and OSATs have sharp-peaked distributions. Table 4 (in Appendix) provides the pairwise Kolmogorov–Smirnov test results and Mann-Whitney test results of the distributions of

Figure 1: Distribution of fixed effects by business model



the efficiency scores shown in Figure 2, both of which indicate that the distributions of the efficiency scores are different in all the pairwise comparisons by the business model. Furthermore, the means and standard deviations of the efficiency scores by business model over the 20 years are shown in Table 5 (in Appendix) and visualized in Figure 3. The curve of annual mean efficiency scores of the fabless firms is conspicuously above the curves of the other business models. A plausible explanation for these results is that although investing in R&D is risky in the semiconductor industry, the fabless business model still has the attraction of lifting the heavy CAPEX burden off the small and medium enterprises' shoulders.

Figure 2: Distribution of efficiency scores by business model

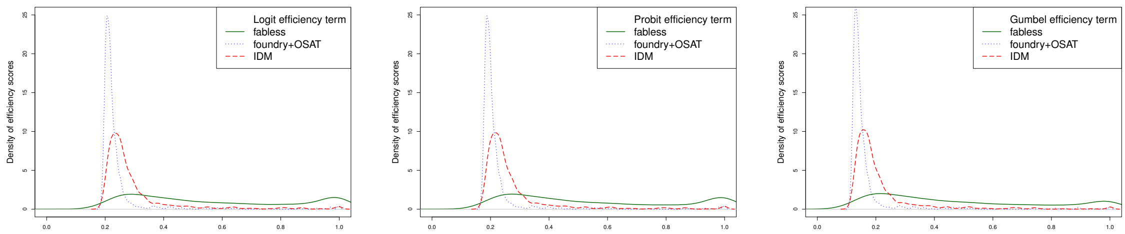
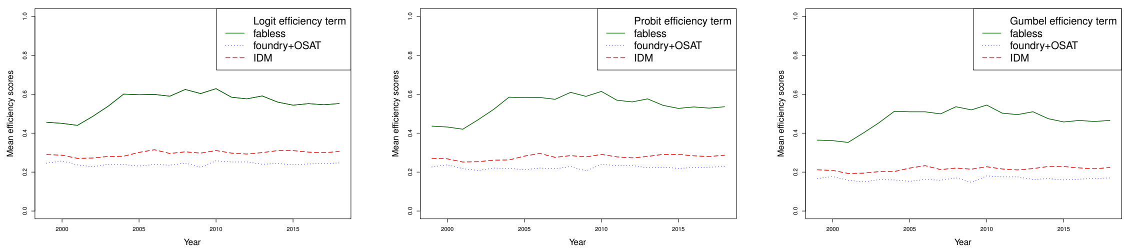


Figure 3: Trends of mean efficiency scores



5 Summary and Conclusions

Comparing the operating efficiency between the vertical integrated IDM model and the specialized fabless-foundry model in the semiconductor industry where diversified companies are producing various products is a vexing problem. This paper applies a panel data stochastic frontier approach which has the advantage of disentangling the firm-level heterogeneity by the within transformation and estimate the efficiency scores by cumulative distribution functions. The nonlinear least squares technique in this approach eschews a priori knowledge of a one-sided inefficiency term present in almost all the existing inefficiency effects models and provides the flexibility to link the efficiency terms with the financial ratios of a firm. The estimation results indicate that the asset-light fabless companies are operating more efficiently than the firms in other operating models in the semiconductor industry. Though the vertical integrated IDMs dominate the semiconductor industry since its early days, the heavy burden of CAPEX and the law of diminishing marginal returns induce more and more companies to embrace the fabless-foundry model. Facing the high uncertainty of commercial success due to technology iteration twisting to the ups and downs in the global economic cycle, the small and medium-sized fabless companies are more flexible and adaptable to market changes in the semiconductor industry.

However, the distinction between the IDM model and the fabless-foundry model is fading away. The vertical specialized fabless-foundry model has the attraction of risk sharing and achieving high capacity utilization so that IDMs also start to contract with other companies to manufacture some of their chips while performing all other remaining tasks internally. The complementarity and integration of the IDMs and the fabless-foundry firms can further expand the range of potential end-user applications for ICs and enable the entire semiconductor industry to thrive and prosper. This developing trend may lead to new business models in the semiconductor industry with higher operating efficiencies in the near future.

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Appendix

Table 4: Tests of difference of the distributions of efficiency scores by business model

	— Logit —		— Probit —		— Gumbel —	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
	Kolmogorov–Smirnov test					
Fabless VS. IDM	0.557^{***}	0.000	0.557^{***}	0.000	0.557^{***}	0.000
Fabless VS. Foundry &OSAT	0.767^{***}	0.000	0.768^{***}	0.000	0.768^{***}	0.000
IDM VS. Foundry &OSAT	0.455^{***}	0.000	0.455^{***}	0.000	0.455^{***}	0.000
	Mann-Whitney test					
Fabless VS. IDM	$2,663,969^{***}$	0.000	$2,664,607^{***}$	0.000	$2,665,456^{***}$	0.000
Fabless VS. Foundry &OSAT	$2,953,105^{***}$	0.000	$2,954,469^{***}$	0.000	$2,955,333^{***}$	0.000
IDM VS. Foundry &OSAT	$247,099^{***}$	0.000	$246,849^{***}$	0.000	$246,711^{***}$	0.000

NOTE. H_0 in the Kolmogorov–Smirnov test is that the two distributions are equal.
H_0 in the Mann-Whitney test is that the two distributions are equal.

Table 5: Mean and standard deviation of efficiency scores

Year	Logit Fabless	Logit Foundry &OSAT	Logit IDM	Normal Fabless	Normal Foundry &OSAT	Normal IDM	Gumbel Fabless	Gumbel Foundry &OSAT	Gumbel IDM
1999	0.456	0.246	0.290	0.436	0.227	0.271	0.364	0.167	0.212
	(0.217)	(0.068)	(0.153)	(0.221)	(0.067)	(0.155)	(0.210)	(0.063)	(0.158)
2000	0.450	0.257	0.290	0.432	0.238	0.268	0.362	0.177	0.209
	(0.232)	(0.106)	(0.147)	(0.235)	(0.104)	(0.149)	(0.222)	(0.096)	(0.151)
2001	0.440	0.237	0.271	0.420	0.218	0.252	0.353	0.158	0.193
	(0.228)	(0.090)	(0.135)	(0.230)	(0.088)	(0.136)	(0.226)	(0.082)	(0.141)
2002	0.487	0.227	0.272	0.469	0.208	0.254	0.402	0.150	0.195
	(0.263)	(0.073)	(0.132)	(0.269)	(0.071)	(0.133)	(0.268)	(0.067)	(0.138)
2003	0.539	0.240	0.281	0.522	0.221	0.262	0.453	0.161	0.202
	(0.274)	(0.096)	(0.133)	(0.281)	(0.094)	(0.134)	(0.283)	(0.087)	(0.138)
2004	0.601	0.239	0.282	0.585	0.219	0.262	0.512	0.160	0.203
	(0.270)	(0.094)	(0.129)	(0.278)	(0.092)	(0.130)	(0.279)	(0.085)	(0.133)
2005	0.597	0.231	0.301	0.582	0.212	0.282	0.510	0.153	0.221
	(0.276)	(0.089)	(0.162)	(0.284)	(0.088)	(0.163)	(0.283)	(0.080)	(0.159)
2006	0.599	0.239	0.315	0.583	0.221	0.296	0.510	0.162	0.233
	(0.271)	(0.112)	(0.176)	(0.278)	(0.115)	(0.177)	(0.277)	(0.110)	(0.171)
2007	0.590	0.235	0.296	0.574	0.217	0.276	0.499	0.158	0.213
	(0.263)	(0.108)	(0.129)	(0.272)	(0.112)	(0.128)	(0.268)	(0.107)	(0.117)
2008	0.625	0.247	0.304	0.610	0.229	0.285	0.536	0.171	0.221
	(0.270)	(0.146)	(0.145)	(0.279)	(0.150)	(0.145)	(0.279)	(0.151)	(0.132)
2009	0.603	0.225	0.298	0.589	0.206	0.278	0.520	0.148	0.215
	(0.287)	(0.059)	(0.138)	(0.296)	(0.058)	(0.138)	(0.298)	(0.054)	(0.126)
2010	0.629	0.258	0.311	0.614	0.240	0.291	0.544	0.181	0.228
	(0.279)	(0.147)	(0.128)	(0.288)	(0.150)	(0.127)	(0.292)	(0.148)	(0.116)
2011	0.584	0.252	0.298	0.570	0.234	0.278	0.503	0.176	0.216
	(0.284)	(0.146)	(0.120)	(0.293)	(0.150)	(0.120)	(0.298)	(0.151)	(0.112)
2012	0.576	0.252	0.293	0.561	0.234	0.273	0.495	0.175	0.211
	(0.281)	(0.145)	(0.113)	(0.290)	(0.148)	(0.114)	(0.298)	(0.147)	(0.104)
2013	0.591	0.240	0.300	0.576	0.222	0.280	0.510	0.162	0.218
	(0.283)	(0.103)	(0.112)	(0.292)	(0.104)	(0.112)	(0.298)	(0.096)	(0.103)
2014	0.560	0.244	0.311	0.543	0.225	0.291	0.474	0.166	0.229
	(0.274)	(0.102)	(0.139)	(0.282)	(0.104)	(0.140)	(0.285)	(0.100)	(0.134)
2015	0.544	0.238	0.310	0.527	0.219	0.291	0.458	0.160	0.229
	(0.275)	(0.086)	(0.143)	(0.283)	(0.088)	(0.144)	(0.282)	(0.080)	(0.137)
2016	0.552	0.242	0.303	0.535	0.223	0.284	0.465	0.164	0.222
	(0.273)	(0.084)	(0.136)	(0.280)	(0.085)	(0.138)	(0.282)	(0.078)	(0.130)
2017	0.546	0.244	0.300	0.529	0.225	0.280	0.460	0.167	0.217
	(0.271)	(0.098)	(0.123)	(0.278)	(0.100)	(0.123)	(0.280)	(0.102)	(0.112)
2018	0.552	0.247	0.306	0.536	0.228	0.287	0.466	0.170	0.224
	(0.280)	(0.104)	(0.158)	(0.288)	(0.106)	(0.160)	(0.287)	(0.109)	(0.147)