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A Nonlinear Growth Analysis of Integrated Device Manufacturers' Evolution to the Nanotechnology Manufacturing Outsourcing

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Abstract

With the increasing cost of setting up a semiconductor fabrication facility, coupled with significant costs of developing a leading nanotechnology process, aggressive outsourcing (asset-light business models) via working more closely with foundry companies is how semiconductor manufacturing firms are looking to strengthen their sustainable competitive advantages. This study aims to construct a market intelligence framework for developing a wafer demand forecasting model based on long-term trend detection to facilitate decision makers in capacity planning. The proposed framework modifies market variables by employing inventory factors and uses a top-down forecasting approach with nonlinear least square method to estimate the forecast parameters. The nonlinear mathematical approaches could not only be used to examine forecasting performance, but also to anticipate future growth of the semiconductor industry. The results demonstrated the practical viability of this long-term demand forecast framework.

Keywords: semiconductor, nonlinear growth model, forecast, inventory

1. Introduction

Worldwide semiconductor industry has undergone several forms of business model change in the last 20 years. Pure integrated device manufacturer (IDM), asset-light IDM, and pure integrated circuit (IC) chip design (fabless) are three distinct types of semiconductor business models. The pure IDM model combines both ICs design and manufacturing functions in one company. The asset-light IDM model maintains an internal manufacturing facility and outsources some process development and product manufacturing to contract foundry companies (foundries) such as Taiwan Semiconductor Manufacturing Company (TSMC) and United Microelectronics Corporation (UMC), whose business consists of producing semiconductors on behalf of other chip companies. The third type is the fabless business model. Fabless companies design their own IC chips while outsourcing all ICs manufacturing to foundries (Fig. 1) [1]. In 1990 to 2010, the revenue market share held by total IDMs went from 99% in 1990 to 91% in 2000 and 78% in 2010, while the total fabless companies' share increased from 1% in 1990 to 9% in 2000 and 22% in 2010 [2]. The rapid decline in IDM market share suggests that the change of competitive landscape makes it hard for IDMs to maintain core competency in both IC design and IC manufacturing. According to the market research firm Gartner, Inc., fabless companies registered a very strong 13% sales compound annual growth rate (CAGR) from 2000 to 2010, followed by foundries (7% CAGR) and IDMs (2% CAGR). In addition, the silicon wafer shipments share held by total IDMs went from 88% in 2000 to 78% in 2010, while the total foundries' share increased from 12% in 2000 to 22% in 2010 [2]. IDMs not only face the problem of keeping up with IC process technology trends, but must

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also confront the fast-rising cost of constructing new manufacturing facilities. The continued cost escalation of semiconductor fabrication facilities, process development, and ICs design has cast a shadow over the future of IDMs. The trend is that an increasing number of IDMs are utilizing the outsourcing model to share resources with foundries, thus, gaining access to the most-advanced production capabilities without investing large amounts of capital or incur the significant costs of developing a cutting-edge manufacturing process.

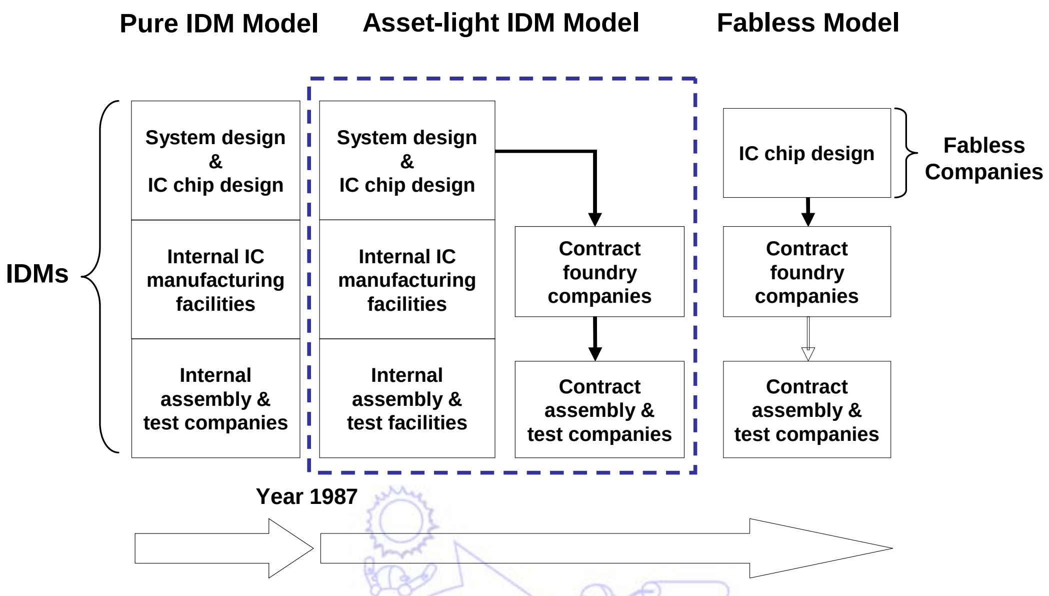

Fig. 1 Semiconductor business models evolution

Most IDM companies' wafer manufacturing facilities are build-to-stock (BTS) operations, focusing on throughput and machine utilization, while foundries' manufacturing facilities are build-to-order (BTO) operations, focusing on due date and cycle time as well as the improvement of customer satisfaction through better achievement of on-time delivery [3-4]. The adopting of the BTO process allows foundry firms to customize customers' products effectively and efficiently. BTO operations create tremendous cost savings of manufacturing, particularly in the areas of reduced raw material and finished goods' inventories, improved flexibility, and increased economies of scale [5]. Foundry's flexibility, wide range of process capabilities, and the benefits of having an established reputation for intellectual property (IP) secrecy attract more IDMs to outsource chip manufacturing to foundries. Foundries benefit from scope efficiencies that could be derived from flexible manufacturing procedures for customized customer products. However, demand fluctuation owing to shortening product life cycle and increasing product diversification in electronics products makes demand forecasting increasingly difficult and complicated. Demand forecast errors cause either inefficient capacity utilization or capacity shortage that will significantly affect the capital effectiveness and profitability of semiconductor manufacturing companies [6]. Therefore, there is an urgent need to develop flexible market intelligence forecasting frameworks that enable foundries to offer timely responses to the constantly changing environment and to maintain robust demand fulfillment strategies.

Nonlinear growth curves have been widely used in the modeling of disciplines, such as consumer durable goods, retail services, agriculture, education, industrial innovations, high technology, administrative innovations, medical innovations, energy-efficient innovation and biology [7]. Zwietering et al. [8] describe many growth phenomena in nature that have sigmoid curves which have similar demand patterns as industries just listed above. In this paper, we use the semiconductor industry as a target to explore more key information about the various capacity decisions that associated with enterprises' decision. This paper aims to construct in a market intelligence framework, a long-term forecast model for foundries' total addressable market (TAM) wafer demand using nonlinear mathematical trend approaches. A market intelligence framework is used to extract information and derive patterns from production and enterprise data to support strategic decisions [9]. To validate the proposed model, an empirical study was conducted in wafer fabrication, in which historical data from semiconductor industry were used to derive trends in wafer demand and to adjust them for inventory levels. Furthermore, we compare forecasting performance of our various nonlinear regression models in order to select our best model. This research first examines the semiconductor manufacturing paradigm shift toward foundry's BTO operations and the trends that accelerate foundry's growth. The long-term impact of manufacturing changes in the semiconductor industry is then discussed. Our empirical analysis of forecasting performance shows that the Gompertz model achieves the best curve fit and forecast capability. This paper sheds new light on a forecast framework in semiconductor industry. Managerial implications and directions for future research are highlighted in the paper.

The paper is organized as follows. In Section 2, we begin with a review of existing literature on trends and constraints in semiconductor manufacturing as well as demand forecasts in the electronics industry. Section 3 lays out the research framework to assess foundries' total addressable wafer demand and sets forth the details of the source data and the forecasting models proposed in this paper. Section 4 discusses the results of the empirical study and how well our forecasts performed. The last section summarizes the findings of this study.

2. The Significance of Demand Forecast

The drive for greater efficiencies and cost reductions has forced many firms to allocate their resources to their core activities. The decision on whether to manufacture in-house or employ external suppliers has always been a fundamental issue for manufacturing [10]. The semiconductor industry has continued technology migration and wafer size enlargement to maintain technology innovation and cost reduction per transistor and thus, achieve unparalleled growth [11]. Assessing the IDM's constraints could provide perspective on semiconductor business trends, in particular, IDM movements toward the foundry business model.

Fig. 2 illustrates that as technology T1 is maturing the technology node, T2 gets introduced. Initially, the defect density and cost per function on T2 are higher than in technology T1. Through yield enhancement efforts, defect density drops rapidly, as volume is ramped up in T2. Technology cross-over occurs when the cost per function in the newer technology is below the cost per function in the older technology [12]. New semiconductor products normally require more advanced nanotechnology processes for their manufacturing. Fast efficient process development has a direct impact on the commercial success of new product introductions. In the semiconductor business, process R&D costs about \$310-\$402 million for 90-65 nanometer (nm), \$600-\$900 million for 45-32nm, and about \$1.3 billion for 22nm, twice that of the 65nm node. Vajpayee

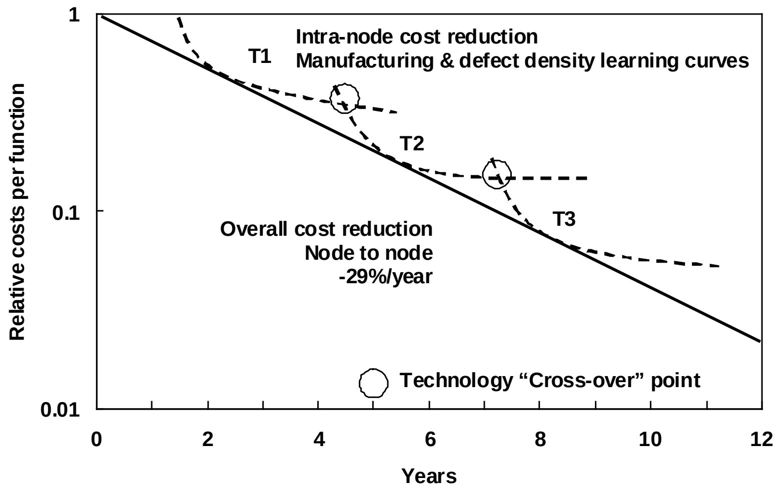

Fig. 2 Cost per function trend and technology "cross-over" points

Table 1 Process technology offerings by committed IDMs and foundries

130nm IDMs	90nm IDMs	65nm IDMs	45nm IDMs	32/28nm IDMs	22/20nm IDMs
Intel	Intel	Intel	Intel	Intel	Intel
Samsung	Samsung	Samsung	Samsung	Samsung	Samsung
IBM	IBM	IBM	IBM	IBM	IBM
STMicro	STMicro	STMicro	STMicro	STMicro	(3)
Panasonic	Panasonic	Panasonic	Panasonic	Panasonic	
Renesas	Renesas	Renesas	Renesas	(5)	
TI	TI	TI	TI		
Toshiba	Toshiba	Toshiba	Toshiba		
Fujitsu	Fujitsu	Fujitsu	Fujitsu		
AMD	AMD	AMD	(9)		
Motorola	Freescale	(10)			
Infineon	Infineon				
Sony	Sony				
Philips	NXP				
Cypress	Cypress				
Sharp	Sharp				
Hitachi	(16)				
Mitsubishi					
Siemens					
ADI	**Foundries**	**Foundries**	**Foundries**	**Foundries**	**Foundries**
Atmel	TSMC	TSMC	TSMC	TSMC	TSMC
On Semi	UMC	UMC	UMC	UMC	UMC
Rohm	Chartered Semi	Chartered Semi	Globalfoundries	Globalfoundries	Globalfoundries
Sanyo	Samsung	Samsung	Samsung	Samsung	Samsung
(24)	SMIC	SMIC	SMIC		

and Dhasmana [13] state only three IDMs (Intel Corporation, Samsung Electronics Co., Ltd., and IBM Microelectronics) could survive this, at and beyond, the 22nm mark. When comparing that to 16 IDMs at the 90nm node, or 10 IDMs at 45nm (Table 1), it is clear that the much-awaited trend of IDM outsourcing to foundries is set to gain more momentum. Thus, foundries, especially larger ones, have benefit of volume lacking in IDMs that reduces defect density and thus can lowers cost. Such cost reductions have been a cornerstone in the success of foundries through the years.

In the global semiconductor industry, producing the right product in the right quantities at a competitive cost is the keystone of innovation. However, the cost of building and equipping manufacturing facilities at various levels of technology increases substantially over time. IDM companies not only face the problem of keeping up with IC process technology trends, but also confront the fast-rising cost of constructing a new wafer fab. A modern semiconductor wafer fabrication facility requires a capital investment of US$2.5-3.0 billion for 90-65nm technologies, US$3.5-4.0 billion for 45-32nm technologies, and US$4.5-6.0 billion for 22-12nm technologies [13]. Table 2 shows that, in 2009, only three semiconductor suppliers had semiconductor capital outlays of US$1.0 billion or more, down from 16 companies only two years earlier in 2007 [14]. The trend is that more and more IDMs are utilizing the outsourcing model to share resources with foundry companies and, thus, gain access to top production capabilities without investing large amounts of capital, or incurring the significant costs of developing a leading-edge manufacturing process themselves. Foundry firms must plan for future customer demand, production schedules and materials requirement to operate efficiently.

Modeling growth of semiconductor sales or demand has received considerable attention in studies of electronics industry dynamics and management of capital investment. There is a huge time-series literature on methods to generate demand forecasts [15]. For example, Norton and Bass [16] modeled diffusion of a new product (demand migration) in the market. Mahajan and Wind [17] surveyed the new product forecasting models. Kurawarwala and Matsuo [18] studied seasonal personal computer demands by Bass function [19]. Victor and Ausubel [20] used a logistic model to examine the global dynamics of eight generations of dynamic random access memory (DRAM) and forecast the market characteristics of

Table 2 "Billion-Dollar Club" for capital spending, 2006-2010

	2006		2007		2008		2009		2010	
Rank	Company	Capex*	Company	Capex*	Company	Capex*	Company	Capex*	Company	Capex*
1	Samsung	$6.8B	Samsung	$8.0B	Samsung	$6.8B	Intel	$4.5B	Samsung	$9.6B
2	Intel	$5.8B	Hynix	$5.1B	Intel	$5.2B	Samsung	$3.5B	TSMC	$5.9B
3	Hynix	$4.8B	Intel	$5.0B	Hynix	$2.9B	TSMC	$2.7B	Intel	$5.2B
4	Toshiba	$3.0B	Micron	$3.7B	Micron	$2.3B			Hynix	$3.0B
5	Micron	$3.0B	Toshiba	$3.6B	Toshiba	$2.2B			Globalfoundries	$2.8B
6	Powerchip	$2.6B	Powerchip	$2.6B	TSMC	$1.9B			Toshiba	$1.9B
7	TSMC	$2.4B	TSMC	$2.6B	SanDisk	$1.6B			Nanya	$1.8B
8	AMD	$1.9B	Nanya	$2.1B	Infineon	$1.3B			UMC	$1.8B
9	Infineon	$1.6B	Elpida	$2.1B					Micron	$1.6B
10	ST	$1.5B	SanDisk	$1.9B					Elpida	$1.2B
11	Fujitsu	$1.4B	Infineon	$1.9B					TI	$1.2B
12	Sony	$1.3B	ProMOS	$1.8B						
13	TI	$1.3B	AMD	$1.7B						
14	Elpida	$1.3B	ST	$1.1B						
15	SanDisk	$1.1B	Spansion	$1.1B						
16	UMC	$1.0B	Fujitsu	$1.0B						

Note: * Capex denotes capital expenditures

the next DRAM generations. Frank [21] adopted a modified logistic model to forecast the diffusion of wireless communications in Finland. Zhu and Thonemann [22] utilized the discrete version of the Bass diffusion model and improved on Kurawarwala and Matsuo [18] model to develop an adaptive forecasting algorithm. Accurate demand forecast could effectively reduce decision uncertainty for capacity planning, including capacity level assessment, capacity allocation and capacity expansion strategies. Any investment in capacity expansion at the wrong stage of life cycle could lead to excess capacity and reduce profitability for the semiconductor companies.

Furthermore, inventory is a significant influencing factor to the volatile semiconductor market. In the macroeconomic literature, two essential theories are often utilized to clarify the role of inventory in the business cycle. The first theory proposed by Blinder [23] is called the production-smoothing theory which assumes that firms hold inventories to smooth the time path of production. By doing so, firms are able to lower average costs of production under demand uncertainty when the cost function is convex. This theory predicts that inventory is countercyclical with respect to sales. The other theory of Kahn [24] on stock-out-avoidance assumes that firms keep inventories in order to prevent losses of opportunity for potential sales. When production takes time and is unable to respond to demand shock immediately, firms have an incentive to over-produce in responding to unexpected demand. It results in pro-cyclical inventory. Hence, understanding inventory change is important for studying the business cycle. Semiconductor companies hold a substantial semiconductor finished-goods inventory in order to smooth out production. From our exploratory study on forecast model practices, little research has been done on semiconductor long-term demand forecasting via our proposed top-down approach by using the nonlinear least square method as well as factoring in inventory effect.

3. The Framework for the Long-Term Wafer Demand Forecast

Foundries make forecasts of different types to help them handle uncertainties. They must plan for future customer demand, production schedules and materials requirement planning in order to operate efficiently. The first step is to identify the objectives. The second step is to plot the observations against time for model selection. The construction of forecast model is an iterative process including selecting suitable model, formulating it, estimating the model parameters, carrying out diagnostic checks and then trying alternative models if necessary. The accuracy of forecasting methods have been compared on different series data [25]. In order to improve forecasting accuracy, good theoretical models need to incorporate factors from real setting to improve its practical value and usefulness.

3.1. Research framework

The semiconductor universe consists of analogue ICs, metal-oxide-semiconductor (MOS) logic ICs, MOS memory ICs, MOS micro components, optoelectronics, sensors, and discrete components. The MOS memory market became commoditized due to standardization, volatile chip price, slow innovation, and excess entry. They have so far been excluded from the foundry addressable market. Two tailwinds will improve foundry growth (Fig. 3). The first is the fabless semiconductor industry, which is expected to grow significantly faster than the semiconductor industry as a whole. The second is IDMs' outsourcing wafer demand, excluding MOS memory products. Fig. 4 presents the framework for building a model of total semiconductor wafer manufacturing TAM for foundries from two different levels which are influencing factors and forecast components. The five influencing factors are as follows:

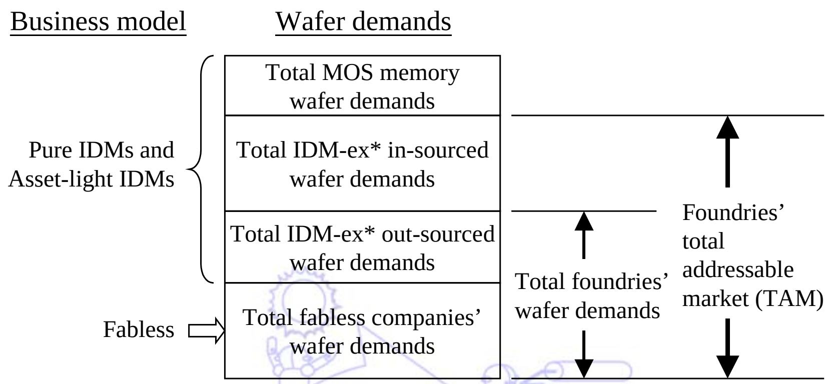

Fig. 3 Foundries' total addressable market

Note: * IDM-ex denotes IDMs' wafer demand excluding MOS memory products

(1) Total semiconductor sales excluding MOS memory products (Semi-ex sales).

(2) Average total semiconductor gross margin excluding MOS memory products (Semi-ex gross margin).

(3) Average total semiconductor days of inventory (DOI) by the end of the year excluding MOS memory products (Semi-ex DOI).

(4) Wafer demand for total foundry companies.

(5) Total IDM, excluding MOS memory products, in-sourced (IDM-ex in-sourced) wafer demand.

Historical and current data for the five influencing factors were used to derive the trends in semiconductor wafer demand and to adjust the inventory fluctuation. IDMs and fabless companies outsource wafer fabrication to foundries. The value of the wafers produced is a subset of the final value of the ICs sold. The cost of purchased wafer from foundries is a portion of semiconductor companies' cost of goods sold (COGS). Available data from some research companies regarding Semi-ex sales, Semi-ex gross margin, Semi-ex DOI, total foundries' historical wafer demands, and total IDM-ex in-sourced wafer demands is used for forecasting the trend of Semi-ex COGS per single wafer. The long-term Semi-ex wafer demand could be simply derived from the result of dividing long-term Semi-ex forecast COGS by the projected COGS per wafer. Moreover, this framework factors in inventory fluctuation and the inventory change. A ratio of COGS to the sum of COGS and inventory change is derived from Semi-ex's sales, gross margin, and DOI. In this ratio, less than one represents the wafer manufacturing firms over-producing in respond to a soft market demand. The over-built wafers flow into inventory. In

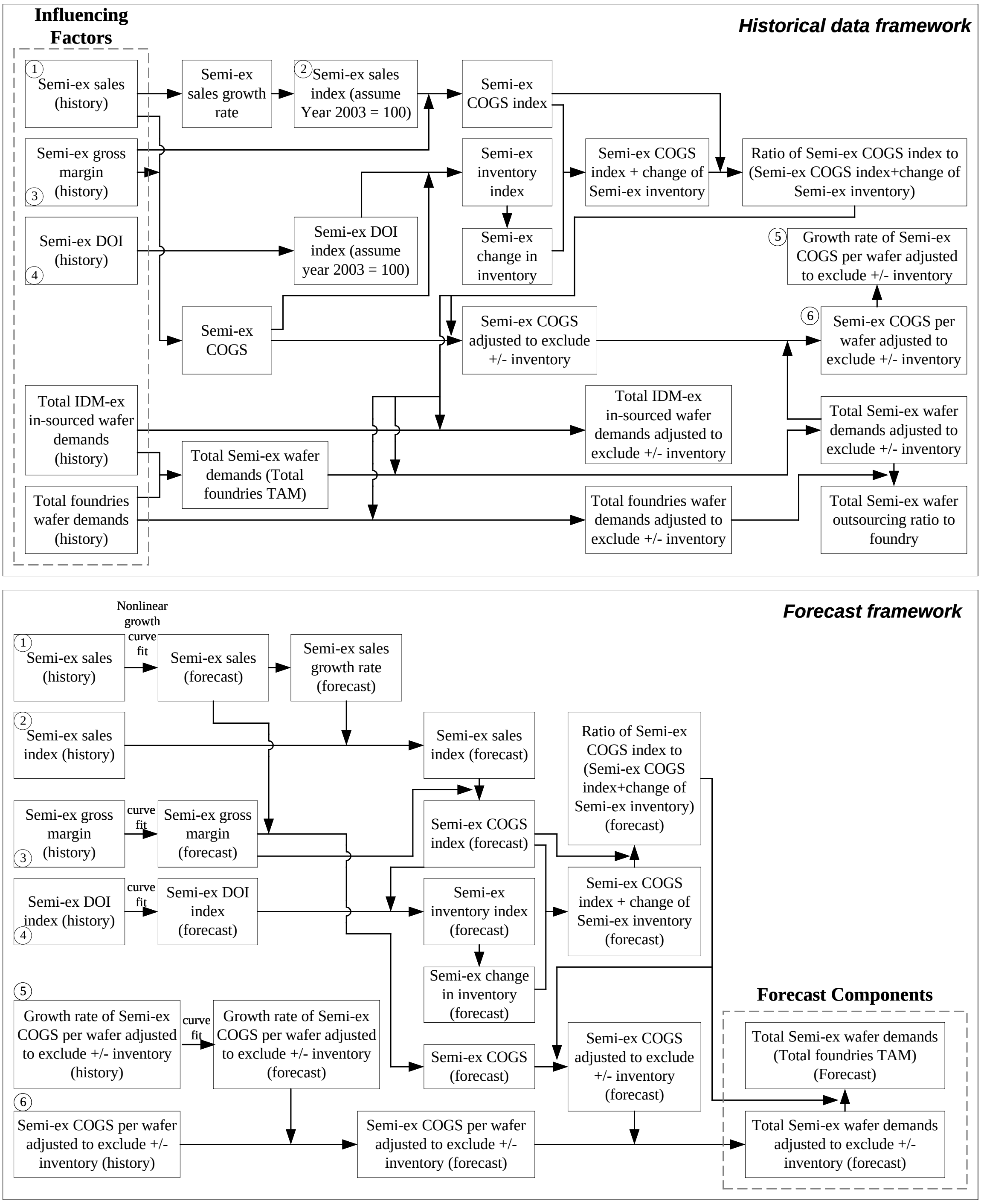

Fig. 4 Framework for the long-term demand forecast of semiconductor total addressable market

Note: Semi-ex denotes semiconductor market excludes MOS memory chip products.

contrast, a ratio over one represents the semiconductor firms under-producing in response to strong market demand. Wafers in inventories are filler for the market demand shortages. Semi-ex's COGS, total foundries' wafer demands, and IDM-ex's in-sourced wafer demand need to be adjusted by some inventory-based adjustment method to exclude inventory effects.

The developed forecasting models of Semi-ex's sales are evaluated by a simple logistic, the Gompertz, and the Chapman-Richards models. Therefore, we could estimate the level of Semi-ex's total addressable wafers contributing to shipments and excluding the influence caused by inventory. The forecast components of our practical long-term demand forecast framework could be effectively derived from the proposed framework.

3.2. Sample and data sources

Industry data are typically provided by trade organizations in order to assure objectivity. In this study, our data sets consist of three sources. Semi-ex's sales, gross margin and DOI are collected form the Global Semiconductor Alliance (GSA). Total foundries' wafer demand and sales from fabless and IDM are drawn from Gartner, Inc., an industry research firm. The selection of sample period, from 2003 to 2010, is based on the longest data availability. Therefore, we have eight observations for each of data set in our study. The worldwide semiconductor sales and MOS memory sales come from the World Semiconductor Trade Statistics (WSTS) published by the Semiconductor Industry Association (SIA). The data set has thirty years of data, covering from 1981 to 2010.

3.3. Nonlinear models for semiconductor sales forecast

(1) Nonlinear growth models

Growth phenomenon of semiconductor sales is a sigmoid curve. Many new forecasting models were proposed based on nonlinear regression models. Three nonlinear mathematical models considered in this study include the simple Logistic [26-27], the Gompertz [28], and the Chapman-Richards [28] models. Background and historical information could be found in the references for further details.

Logistic model $$y(t) = L/\left(1 + ae^{-bt}\right) \tag{1}$$

Gompertz model $$y(t) = Le^{-ae^{-bt}} \tag{2}$$

Chapman-Richards model $$y(t) = L(1 - ae^{-bt})^{\frac{1}{1-f}} \tag{3}$$

For all models considered, y is the dependent growth variable, t is the independent variable, L, a, b, and f are parameters to be estimated, e is the exponential function, and *ln* is the natural logarithm. Khamis et al. [29] notes that the parameters for the growth curve models considered in this paper are defined as follows: L is the asymptote or the possible maximum of the response variable; a is the biological constant and could be specified by evaluate the models at the start of growth when the predictor variable is zero; b is the parameter governing the rate at which the response variable approaches its potential maximum; and f is the allometric constant.

(2) Analytical process

In order to test the forecast accuracy of the simple logistic, the Gompertz, and the Chapman-Richards models, the analytical process is divided into two steps.

Step 1: Model estimation

The first step is used to estimate the models. After reserving the last five data points to test forecast accuracy of the selected nonlinear growth models, the remaining data points were used to fit the three models. The coefficients of the models are estimated by using nonlinear least squares with STATISTICA statistical software. After the coefficients were computed and the models were fitted, the estimated values were calculated.

Step 2: Fit and forecast performance

The nonlinear equations were fitted to growth data by nonlinear regression with a Levenberg-Marquardt algorithm. This algorithm seeks the values of the parameters that minimize the sum of the squared differences between the values of the observed and the predicted values of the dependent variable. The Levenberg-Marquardt nonlinear regression procedure available in STATISTICA 9 [30] was used to demonstrate the method of parameter estimation by using the datasets of observations.

The program then calculated the set of parameters with the lowest residual sum of squares and their 95% confidence intervals. The coefficient of determination (R^2) and root mean square error (RMSE) are used to measure performance as recommended in the literature. Comparison of RMSEs is one useful approach to determine forecasting accuracy between competing models. For forecast performance, the models are used to forecast the last five data points of the datasets. The accuracy of out-of-sample forecasts is evaluated by the mean absolutely percentage error (MAPE). The mathematical representations are shown below:

$$RMSE = \sqrt{\left(\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2\right)/n} \tag{4}$$

$$MAPE = \left(\left(\sum_{t=1}^{n}\left|\left(Y_t - \hat{Y}_t\right)/Y_t\right|\right)/n\right) \times 100\% \tag{5}$$

where Y_t is the actual value at time t, $\hat{Y}_t$ is the estimate at time t, and n is the number of observations. These measurements are based on the residuals, which represent the distance between real data and predictive data. Consequently, if the value of the residuals is small, the fit and prediction performance is considered acceptable. Nonlinear models yielded plausible prediction values when MAPE is low. According to Lewis [31], MAPE is an effective index to evaluate forecasting performance. A forecast with MAPE less than 10% is considered an excellent fit, those between 10% to 20% as good fits, those between 20% to 50% as reasonable fits, and over 50% as incorrect fit.

Moreover, if a three-parameter model is sufficient to describe the data, it is recommended over a four-parameter model because the three-parameter model is simpler and therefore, it’s easier to use and because the three-parameter solution is more stable since the parameters are less correlated.

4. Results and Discussions

Thirty time-series datasets describing worldwide semiconductor revenues and MOS memory sales were collected to test the forecast accuracy of the simple logistic, the Gompertz, and the Chapman-Richards models. Since the sample period for these data is bigger than 30 years, both time series datasets are quite valid if the predicted sample period about 5 years is correctly identified. Table 3 presents the estimated sample period, predicted sample period, and the fitting and forecasting performance for the data set of worldwide semiconductor sales excluding MOS memory.

Table 3 Fitting and forecasting performance ranks of three nonlinear regression models

Year	Semi-ex actual sales (US$ Billion)	Logistic	Gompertz	Chapman-Richards
Estimated sample period: 1981-2005				
1981	7.7	9.0	6.2	6.2
1982	7.7	10.7	8.2	8.2
1983	9.3	12.8	10.7	10.7
1984	20.8	15.3	13.6	13.6
1985	17.8	18.2	17.1	17.1
1986	22.4	21.6	21.1	21.1
1987	27.1	25.5	25.6	25.6
1988	34.1	30.0	30.7	30.7
1989	34.5	35.1	36.4	36.4
1990	38.7	40.9	42.5	42.5
1991	42.4	47.4	49.2	49.2
1992	45.0	54.5	56.3	56.3
1993	56.0	62.3	63.8	63.8
1994	69.4	70.7	71.6	71.6
1995	90.9	79.5	79.8	79.8

Table 3 Fitting and forecasting performance ranks of three nonlinear regression models (Continued)

Year	Semi-ex actual sales (US$ Billion)	Logistic	Gompertz	Chapman-Richards
1996	95.9	88.6	88.2	88.2
1997	107.9	98.0	96.8	96.8
1998	102.6	107.3	105.5	105.5
1999	117.1	116.6	114.3	114.3
2000	155.2	125.5	123.1	123.1
2001	114.1	134.0	131.9	131.9
2002	113.7	141.9	140.7	140.7
2003	133.9	149.2	149.3	149.3
2004	165.9	155.9	157.8	157.8
2005	179.0	161.9	166.1	166.1
R^2		0.952	0.953	0.953
RMSE		11.4	11.3	11.3
Rank of fit		2	1	1
Predicted sample period: 2006-2010 (out-of-sample)				
2006	189.2	167.2	174.1	174.1
2007	197.8	171.9	182.0	182.0
2008	202.3	175.9	189.6	189.6
2009	181.5	179.4	197.0	197.0
2010	228.7	182.5	204.1	204.1
MAPE		11.8%	8.3%	8.3%
Rank of predict		2	1	1
Forecsting Power*		good	excellent	excellent

Note: * A forecast with MAPE less than 10% is considered an excellent fit, those between 10% and 20% as good fits, those between 20% to 50% as reasonable fits, and those over 50% as incorrect fits.

The evaluation rule is that the larger the value for R^2 and the smaller the value for RMSE, the better the fit performance is. All models have considerably high R^2 values. The best fit models are the Gompertz and Chapman-Richards models because of the highest R^2 value (0.953) and RMSE value (11.300). In addition, the Gompertz and the Chapman-Richards

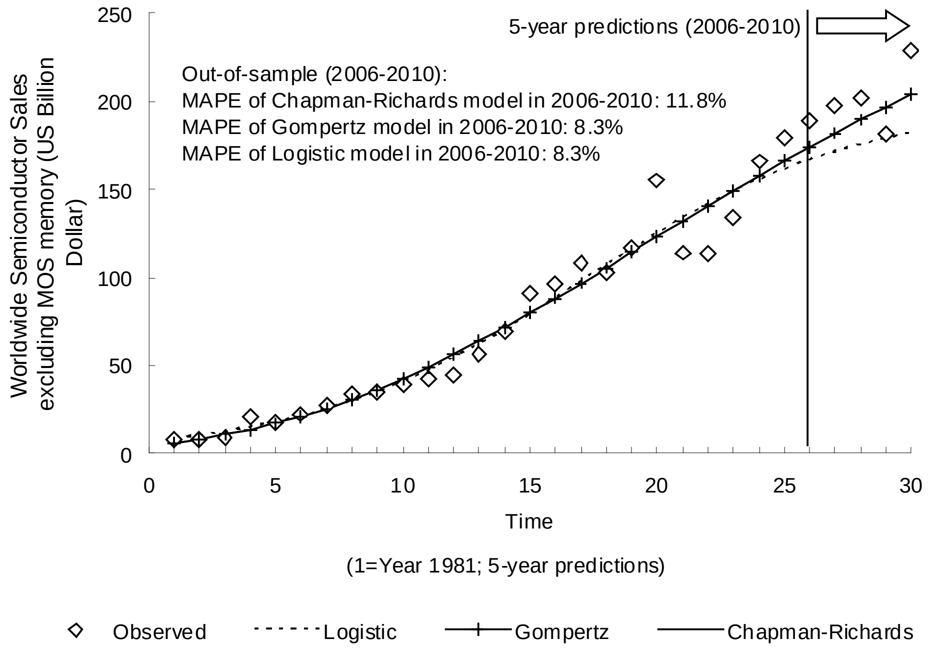

Fig. 5 Growth curves of actual and predicted worldwide semiconductor sales excluding MOS memory products for three nonlinear regression models with 5-year predictions

models accurately predict worldwide semiconductor sales with a smaller MAPE value (8.3%) than the simple Logistic model for the out-of-sample data from 2006 to 2010 (Fig. 5). The smaller the value for MAPE, the better the prediction performance is. Furthermore, it is recommended to describe the data by the three-parameter Gompertz model over the four-parameter Chapman-Richards model because the three-parameter model is simpler and easier to use. Thus, the Gompertz model is best model that we are looking for. As a result, we note that the total semiconductor sales excluding MOS memory for 2010, globally, are expected to be US$229 billion and should enjoy a 3.4% CAGR over 2010-2015, and 2.9% CAGR from 2010 to 2020 based on the Gompertz model forecast.

Bringing together five influencing factors versus the implied semiconductor wafer demand growth in the proposed forecast framework as shown in Fig. 4, we can estimate the level of semiconductor wafer demand implicit in projections. There remain elements of assumptions here, but in most cases, we notice that our semiconductor forecast framework needs simply to revert back to its levels from 2003 to 2007 to meet the forecast assumptions due to an unusual severe downturn in 2008 to 2009. Table 4 shows the results of the estimating semiconductor's total addressable wafer market. Row 11 shows inventory ratio from 0.94 to 1.05 in 2003 to 2010. It represents inventory smooth out the semiconductor shortage and oversupply ranges from -6% to 5%. The fluctuations of volatile semiconductor demand make the inventory factor important. The results show the practical viability of employing the proposed framework for long-term demand forecast. It considers an inventory factor to enhance the decision quality for foundry's capacity planning, i.e., to reduce the risks of capacity shortage or surplus.

Moreover, the rapid growth of fabless production and the rise of IDM wafer outsourcing to foundries would have a direct bearing on increasing the semiconductor TAM for foundries. The total foundry long-term forecast demand relied on

Table 4 Estimating semiconductor total addressable wafer demands, 2003-2010

Row	Items	2003	2004	2005	2006	2007	2008	2009	2010
1	Semi-ex* sales (US$ billion)	134	166	179	189	198	202	182	229
2	Semi-ex sales growth rate (%)	18%	24%	8%	6%	5%	2%	-10%	26%
3	Semi-ex sales index (assume Yr2003 = 100)	100	124	134	141	148	151	136	171
4	Semi-ex gross margin (%)	45%	47%	47%	46%	45%	47%	45%	51%
5	Semi-ex COGS (US$ billion)	74	88	95	103	110	108	100	111
6	Semi-ex COGS index (= semi-ex sales index x (1 - semi-ex gross margin))	55	66	71	77	82	80	75	83
7	Semi-ex EOY wafer DOI (assume Yr2003 = 100)	100	98	93	103	93	102	93	105
8	Semi-ex inventory index (= (semi-ex DOI x Semi-ex COGS) / 360)	15	18	18	22	21	23	19	24
9	Change of semi-ex inventory	2.4	2.6	0.4	3.7	-0.8	1.5	-3.5	5.0
10	Semi-ex COGS index + change of semi-ex inventory	57	68	72	81	81	82	71	88
11	Ratio of semi-ex COGS index to (semi-ex COGS index + change of semi-ex inventory)	0.96	0.96	0.99	0.95	1.01	0.98	1.05	0.94
12	Semi-ex COGS adjusted to exclude +/- inventory (US$ billion)	71	84	95	98	111	106	105	105
13	Semi-ex COGS per wafer adjusted to exclude +/- inventory (US$)	1,304	1,368	1,353	1,323	1,223	1,100	1,232	1,107
14	Semi-ex COGS per wafer adjusted to exclude +/- inventory growth rate (%)	-2%	5%	-1%	-2%	-8%	-10%	12%	-10%
15	Semi-ex wafer shipments (8"-eq. Mpcs†)	57	64	70	78	90	98	81	100
16	Semi-ex wafer shipments growth rate (%)	12%	13%	10%	11%	15%	9%	-17%	24%
17	Semi-ex wafer shipments adjusted to exclude +/- inventory (8"-eq. Mpcs)	54	62	70	74	91	96	85	95
18	Of which: IDM-ex‡ in-sourced wafer shipments adjusted to exclude +/- inventory (8"-eq. Mpcs)	43	47	53	55	68	73	63	66
19	Of which: Total foundry wafer shipments adjusted to exclude +/- inventory (8"-eq. Mpcs)	11	15	17	19	23	23	22	29
20	Semi-ex wafer outsourcing ratio to foundry (%)	19%	23%	24%	25%	26%	24%	27%	29%

Note: * Semi-ex denotes the total semiconductor excluding MOS memory market segment, † 8"-eq. Mpcs denotes million pieces 8" equivalent wafers, and ‡ IDM-ex denotes the total IDMs excluding MOS memory.

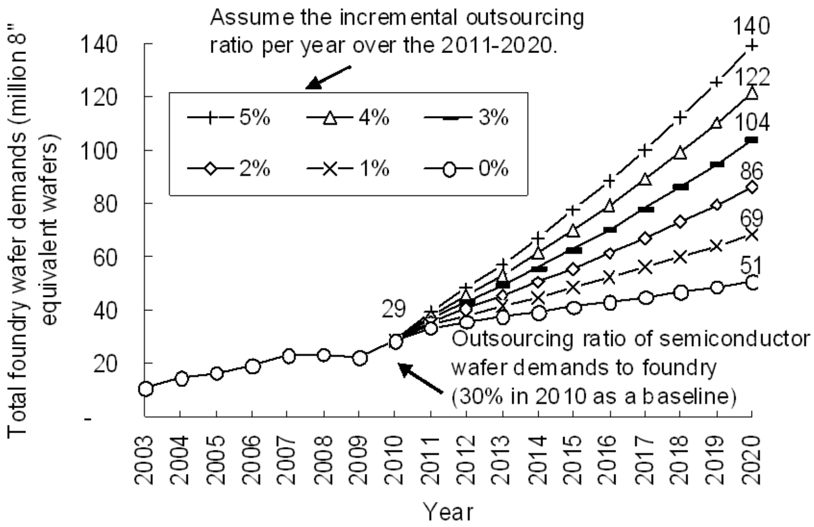

Fig. 6 Total foundry wafer demands, 2003-2020

the result of multiplying the total semiconductor wafer TAM by the semiconductor wafer outsourcing ratio to foundries. Row 20 presents an outsourcing ratio gain of ten percentage points from 20% in 2003 to 30% in 2010 as shown in Table 4. We assume the 30% outsourcing ratio in 2010 as a baseline and make an incremental outsourcing ratio assumption over the 2011 to 2020 time-frame from flat to 5% outsourcing ratio increase per year. Curves in Fig. 6 represent the total semiconductor wafer demand outsourced to foundry firms in 2003 to 2020. The flat outsourcing ratio assumption in 2011 to 2020 shows that total foundry wafer demand is forecast to grow to 51 million eight-inch (8”) equivalent wafers in 2020 from 29 million 8” equivalent wafers, a 2010 to 2020 CAGR of 6% as compared to 12% CAGR from 2005 to 2010. In addition, the assumption of 5% outsourcing ratio increase per year in 2011 to 2020 reflects the total foundry wafer demand forecast to grow to 140 million 8” equivalent wafers in 2020, in which the outsourcing ratio of semiconductor wafer to foundry increases to 79% in 2020 from 30% in 2010. The rise of fabless business and an unstoppable movement for IDMs toward an asset-light business model are two further tailwinds to foundry expansion in the coming future. Therefore, total foundry long-term wafer demand forecast can be derived from the domain knowledge judgment for the long-term strategic capacity decisions.

5. Conclusions

Aggressive outsourcing by IDMs (asset-light business model) and working more closely with foundries are new trends in the semiconductor manufacturing industry. The rising of IDM wafer fabrication outsourcing to foundries is a significant tailwind to the growth of foundry businesses. This study proposes a market intelligence long-term demand forecasting framework for foundries which is constructed by using the five influencing factors of historical semiconductor market data sets, including Semi-ex sales, Semi-ex gross margin, Semi-ex DOI, total foundry wafer demand and total IDM-ex in-sourced wafer demand. The nonlinear growth model-fitting result of Semi-ex sales has shown that the Gompertz model performs excellent MAPE and outperforms the simple Logistic and the Chapman-Richards models. The selected Gompertz model enables to anticipate Semi-ex sales growth, and consequently enables to forecast the total foundry wafer demand with different scenarios of Semi-ex wafer outsourcing ratios to foundry.

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