Benchmarking the Productivity of Photomask Manufacturers

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ABSTRACT

A survey-based, empirical study that benchmarks the productivity of photomask manufacturers has led to some significant conclusions. Firstly, the wide variation in the productivity indicators from company to company suggests that all participants may have significant cost-reduction opportunities within their operations -- even among the best performers capital is underutilized. Secondly, the high downtime of pattern generation tools is limiting productivity. Thirdly, producing smaller feature sizes is correlated to an investment in engineering and experimentation capacity. It could not be confirmed that photomask manufacturers are successfully taking advantage of economies of scale, suggesting that the outlook for profitability of many photomask manufacturers is precarious.

Keywords: Benchmarking, Photomask, Manufacturing, Productivity

1. INTRODUCTION

For the past four decades, Moore's Law [1], which states that the number of transistors that can be built into a given amount of chip space will double every 12 to 18 months, has been driving the dimensions of merit for semiconductor manufacturing and its enabling technologies. Foremost among these enabling technologies is optical projection microlithography, which faces the particularly daunting challenge of resolving integrated circuit features whose dimensions shrink by 30% every two to three years [2, 3]. Historically, this feat was achieved by embodying light sources with progressively shorter wavelengths and lenses with higher numerical apertures in lithographic projection tools. However, these efforts have not kept pace with the requirements of Moore's Law since in the mid-1990s, when the minimum feature sizes of integrated circuits first shrank below 0.5 µm. At that point in time, optical projection micrllithography was pushed into the "sub-wavelength" domain, where lithographic projection tools print features that are significantly smaller than the wavelength of the light source [3-5].

"Sub-wavelength lithography" could only be achieved by introducing technologies such as optical proximity effect correction (OPC) and phase shift masks (PSMs), which have driven up the cost and complexity of photomask manufacturing beyond what could be expected from Moore's law. OPC in particular introduces ultra-small sub-resolution features into a mask, which compensate for how light modifies a mask pattern when it reaches the wafer. These extra features dramatically increase the data size associated with a mask, driving up the time required to write and inspect the mask [5]. Phase shift masks (PSMs) enhance contrast to expose the photoresist and print features at resolutions that cannot be achieved with conventional binary masks (for any particular commercially available combination of source wavelength and numerical aperture). However, when compared to binary masks, PSMs require more sophisticated and expensive starting material (mask blanks) [6, 7], and the process for producing PSMs is more complex and more costly [8].

Photomask manufacturers are struggling with the cost of producing photomasks, which has increased from ~US$ 500k for the 130 nm technology node to ~US$ 1 million for the 90 nm node and to ~US$ 2 million for the 65 nm node [8–19]. Cost escalation is likely to continue beyond the 65-nm technology node, even though semiconductor manufacturers, the buyers of photomasks, have indicated that the price of photomasks is stretching the limits of what they are willing to pay. Suppliers of photomasks are thus actively looking for ways to reduce the cost of producing photomasks, which can be achieved by increasing the productivity of photomask manufacturing [20].

This paper describes an empirical study that investigates the productivity of photomask manufacturing. We (the authors of this paper) identify key productivity indicators that drive photomask manufacturing, and we propose a set of candidate factors, whose characteristics potentially influence the behavior of these productivity indicators (§2). In §3, we explain the research methods we use to explore the relationships between productivity indicators and candidate factors. We have deployed a survey instrument and use analytical methods that protect the anonymity of photomask manufacturers that have participated in the study. To provide insight beyond what can be revealed by quantitative methods, we have conducted interviews with experts employed by photomask manufacturers, by their customers and by their suppliers. The results of the study and its implications for the stated productivity indicators are presented in §4. In §5, we summarize our results, explain some of the limitations of the study in this paper and make recommendations for further research.

2. PRODUCTIVITY INDICATORS

Productivity tends to be given in terms of indicators that reflect returns on particular sets of investments, which do not necessarily have to be expressed in financial terms. For example, in a mask shop the number of mask writing, etching, inspection and other tools, as well as the area of clean room space, can act as proxies for a photomask manufacturer’s investment in physical capital; the number of engineers involved in the manufacturing process can act as an indicator of investment in intellectual capital; the number of engineering (non-production) plates processed may reflect an investment in experimentation that leads to improved quality; and the number hours of scheduled downtime may act as an indicator of an investment that leads to improved capital productivity by reducing the amount of unscheduled downtime. Yields, the fraction of time equipment is producing sellable photomasks, and the number of sellable photomasks produced per unit time all constitute indicators for return on investment. Productivity can be inferred from dividing indicators of return on investment by indicators of investment. For example, in the absence of cost data, the product output rate (the number of plates shipped per unit time) per employee is an indicator of the productivity of human capital. The product output rate per pattern-generating (PG) tool constitutes a measure of the productivity of physical assets.

Of particular interest to photomask manufacturers are economies of scale, which have been shown to be key to achieving profitability in this industry [20]. Economies of scale are observed when a product's unit cost declines or when productivity metrics increase as the absolute volume produced per period increases [21]. (A firm enjoys economies of scale when it is able to double its output at less than twice the cost [22].) For example, observing that the product output rate per PG tool is proportional to the number of PG tools in a mask shop or observing that the product output rate per full time equivalent (FTE) employee is proportional to the number of FTE employees in the mask shop both constitute evidence of economies of scale.

Productivity in photomask manufacturing is also a function of the type of products a photomask manufacturer produces. A mask maker that generates plates for the 250-nm node and above will have to master fewer resolution enhancement techniques (RETs) and make fewer investments than one who primarily generates plates for the 130-nm node and below. The technologically less advanced photomask manufacturer will also be able to produce and inspect more plates per unit time than the technologically more sophisticated one. Productivity metrics for the less sophisticated manufacturer should thus exhibit higher values than those for the more sophisticated one.

$$\tau = [500\ x_{>350} + 350\ x_{350} + 250\ x_{250} + 180\ x_{180} + 130\ x_{130} + 90\ x_{90} + 65\ x_{\leq 65}]^{-1} \qquad (1)$$

Equation (1) provides a technology index (τ) that estimates the technological sophistication of a mask shop from its product mix and expresses it in terms of nm^{-1}. The variables $x_{>350}$, x_{350}, x_{250}, x_{180}, x_{130}, x_{90} and $x_{\leq 65}$ respectively represent the fraction of the mask shop's business that is associated with the corresponding technology nodes. Mask shops that produce a greater proportion of plates with small geometries rate commensurately higher on the technology index. The numerical values of the variables in equation (1) can be obtained from Sematech's annual mask industry assessment survey [12-15].

3. CONFIDENTIALITY-DRIVEN RESEARCH METHODS

Data for the empirical study in this paper come from a set of 79 productivity-oriented questions that were attached as a supplement to Sematech's 2005 survey of photomask manufacturers [14]. These questions fell into two broad categories: operating cost factors (section 6 of the survey) and equipment utilization (section 7 of the survey). Questions regarding operating factors solicited quantitative information about clean room space, operating personnel and engineering support. Questions regarding equipment utilization solicited quantitative information about the output of product plates, the output of engineering plates, scheduled equipment downtime and unscheduled equipment downtime. Questions in all categories were highly differentiated to enable a detailed breakdown of the results with respect to factors such as clean room class, direct labor, various engineering efforts (process control, yield, maintenance/installation, R&D/new product development, data processing and sustaining) and 15 equipment categories.

Participation in the study was very encouraging, indicating that the interest in this subject among photomask manufacturers is very strong. Seven major global merchant and captive mask manufacturers, whose combined revenue represented more than 75% of the global mask market in 2005, participated in the survey and answered the majority of questions. While there was some misinterpretation of some of the questions, and most participants did not answer all questions, the response was generally quite good. The survey provided very useful information relating to the cost structure and productivity of mask shop operations.

Analysis of data from the 79 productivity-oriented questions and data from the technically oriented companion survey [14] have yielded 79 cost-related or productivity-oriented indicators, which are displayed in tables A1 through A5 of the appendix to this paper. The label ‘n’ in these tables identifies a column that denotes the number of observations (non-zero responses) that pertain to each indicator. The label ‘Avg.’ identifies a column that denotes the average value (arithmetic mean) obtained from these responses. All indicators in tables A1 through A5 are normalized to assure the anonymity of the participants.

The need for confidentiality prevents us from displaying normalized, anonymous data graphically, because it is feared that sophisticated industry analysts could determine the identity of a survey participant from such data. For all indicators, variability is given in terms of range ratios, in which the largest data point in a sample is assigned a value of 1 and the other data points in the sample are scaled proportionally. For example, a normalized version of equation (1) assesses the technological sophistication of the participants from their respective product mixes. The participating mask shop, which on average produces photomasks with the smallest feature sizes, is assigned a technology index of 1. The technology index for all other participants is normalized proportionally. The smallest normalized value in the sample denotes the range ratio.

In our analysis, the relationship between two normalized indicators is determined by least squares regression in which both the dependent variable ‘y’ and the independent variable ‘x’ are normalized such that the largest value in the data range and data domain is set to 1 and all other values are scaled accordingly. The relationship between x and y is expressed in terms of a linear equation of the form y=ax+b, where the coefficient ‘a’ represents the expected value of the slope of the line and ‘b’ denotes the expected value of the line’s intercept. Key regression parameters and important results of analysis of variance (ANOVA) are presented in tabular form. Acronyms represent key statistical terms in these tables: R2 → R square; AR2 → Adjusted R square; SE → Standard Error; n → number of observations; coef. → coefficient (expected value of a or b); and t-stat → t statistic. The quantity ‘1-p’ stands for the probability that the actual value of a (or b) is greater than 0, given that the expected value of a (or b) is greater than 0. (Alternatively, 1-p stands for the probability that the actual value of a (or b) is less than 0, given that the expected value of a (or b) is less than 0.) A result is considered significant, if the chances are at least 80% that the absolute value of the slope the regression line |a| does not equal 0, i.e. $1\text{-}p \geq 0.80$.

The need for confidentiality in this study has limited the statistical significance of its results. Not all participants have answered all questions, which has forced the authors to work with samples sizes ranging from 3 to 7. Only a small fraction of many possible conclusions could be made with a confidence of 0.80 or greater. Consequently, the findings of this study have been validated in interviews with 25 experts in photomask manufacturing, photolithography, VLSI circuit manufacturing, VLSI circuit process development, tool development, materials development and related technical fields. These experts have been recruited by recommendations from within their respective peer groups.

4. RESULTS AND IMPLICATIONS

Upon data analysis, a number of results, which are itemized below, are potentially important to photomask manufacturers and their customers, the semiconductor manufacturers. The implications of each result are discussed as the result is presented.

4.1 General Observations

Table 1 illustrates that a high degree of variability was observed in many indicators. Variations exceeding an order magnitude between the mask shop with the highest value and the one with the lowest value were quite common. This suggests that all participants may have significant cost-reduction opportunities within their operations.

Table 1. Range Ratios for Selected Variables

Variable	Range Ratio (S/L)
Plates Shipped per FTE Employee	0.087 : 1
Plates Shipped per FTE Engineer	0.010 : 1
Engineering Plates/Plates Shipped	0.053 : 1
Scheduled Downtime: Laser PG	0.083 : 1
Unscheduled Downtime: Laser PG	0.017 : 1

Table 1 shows that the number of masks shipped per FTE employee vary by more than an order of magnitude, and masks shipped per FTE engineering employee vary by nearly two orders of magnitude. It is expected that some variation would be observed as a consequence of the differences in the business structure of the responding mask shops. However, a variation this large indicates that staffing strategies and average labor content per mask among mask vary widely from mask shop to mask shop. In addition, table A1 in the appendix indicates that the engineering effort in mask making is asymmetric. The investment in maintenance and installation, R&D, new process development and sustaining is significantly higher than the investment in process control, yield and data processing. A senior mask-making engineer with semiconductor manufacturing experience provides an explanation for this finding.

> *"Systematic defects tend to dominate mask making more than chip making. … Many systematic problems come from the equipment, and most process control problems occur during the early part of the lifecycle. So it makes sense for a mask shop to invest heavily in equipment engineering and process development. … Semiconductor processes consist of up to an order of magnitude more steps than photomask processes. So it makes sense for chipmakers to invest more in trying to localize the problem to a particular process step or piece of equipment. This means that the chipmakers will have more people working in yield and process integration groups than the mask makers. They can also afford more because they are in an industry with a larger market."*

Table 2 indicates that investments in engineering can pay off. The yield of attenuated phase shift masks (PSM) correlates to the number of FTE engineering employees (1-p=0.80). No other correlation between yield and the various investments in engineering could be established, in part because of the small sample of survey participants and in part because the yield of binary masks was homogeneously high. We also observed no significant correlation between yield and the fraction of the mask shop containing a Class 1 clean room.

Table 2. Yield (Attenuated PSM) vs. Number of FTE Engineering Employees

Regression Statistics	R^2	AR^2	SE	n
	0.904	0.807	0.123	3
ANOVA	Coef.	SE	t-stat	1-p
Intercept 'b'	0.409	0.138	2.97	0.79
Slope 'a'	0.528	0.172	3.06	0.80

A variation of approximately one order of magnitude has been observed in the number of plates shipped per tool. Unfortunately, there is insufficient data from the questionnaire to ascertain what portion of this variation is due to market-related limitations in mask production and what portion is due to differences in mask shop management procedures. Some mask shops ran a very large fraction of engineering plates (more than 25%), whereas others ran only a few percent. In either case, most such plates were run on vector-shaped e-beam pattern generation (PG) tools operating at or above 50KV; the critical dimensions of most of these plates were measured using MUV tools; and most were inspected using die-to-die inspection tools.

The responses to the survey indicate strikingly high values for both scheduled (table A4) and unscheduled (table A5) downtime of pattern generation (PG) tools. This impacts mask-making productivity very highly, because PG-tools have a very high cost of ownership, and they tend to limit the mask shop's throughput. While some portion of this downtime can probably be addressed by the mask shops through improved procedures, it is likely that much of the downtime is characteristic of the tool employed and therefore must be addressed by the PG tool supplier. A significant reduction of costs resulting from unscheduled downtime could be achieved if the PG tool manufacturers were able to improve their reliability. However, a manager employed by a supplier of PG tools explains why improving the reliability of these tools could become a major challenge.

> *"Our customers consistently push the performance of PG tools beyond their specified limits, especially in the early stages of process development. Under these circumstances, it is difficult for a PG-tool to be very reliable."*

4.2 Capital Utilization

A significant number of mask shops in our sample estimate the mask shop's utilization of capital in terms of the yield rate

$$U(t) = Y_{up}(t)\, Y_{ru}(t)\, Y_{pp}(t)\, Y_{ln}(t)\, Y_{nr}(t), \qquad (2)$$

where $Y_{up}(t)$ is the fraction of time that capital equipment is not undergoing scheduled or unscheduled maintenance; $Y_{ru}(t)$ is the fraction of time available equipment is actually running; $Y_{pp}(t)$ represents the proportion of plates running are production plates; $Y_{ln}(t)$ is the fraction of production plates that are not scrapped during the manufacturing process; and $Y_{nr}(t)$ denotes the fraction of non-scrapped production plates that are not reworked [20]. (This definition is consistent with operations research approaches to waste reduction that are described in [23-26].) The results of the survey show that PG tools are the primary limiters from the point of view of equipment downtime. Thus, for the purposes this paper, $Y_{up}(t) = 1 - (W_{sched\text{-}PG} + W_{unsch\text{-}PG})$, where $W_{sched\text{-}PG}$ and $W_{unsch\text{-}PG}$ respectively denote the fraction of time (waste rate) that PG tools are down for scheduled and unscheduled maintenance.

Judging from the results of the 2005 Mask Industry Assessment survey [14], Tables A2 through A5, and comments given by the respondents in this study, the values for the constituent factors to capital utilization during volume production at the most productive photomask manufacturers can be estimated somewhat optimistically as $Y_{up}(t) = 0.9$; $Y_{ru}(t) = 0.95$; $Y_{pp}(t) = 0.9$; $Y_{ln}(t) = 0.9$; and $Y_{nr}(t) = 0.95$. Substituting these values into equation (1) gives $U(t) = 0.66$, which indicates at least one-third of all resources in photomask manufacturing is wasted. The causes of this waste have been analyzed successfully over the years [12-16, 20].

4.3 Economies of Scale

The output in plates per year of the largest participating photomask manufacturer has exceeded the output of the smallest one by more than an order of magnitude. This finding motivated us to investigate whether photomask manufacturing is subject to economies of scale with respect to human capital and physical capital. In response, we ran the following regressions: 1) product output rate per FTE employee versus number of FTE employees; 2) product output rate per non-exempt FTE employee versus number of non-exempt FTE employees; and 3) product output rate per "big ticket item" (BTI) versus number of BTIs in the mask shop. (PG tools and an inspection tools were considered big ticket items. They tend to be the most expensive tools in the mask shop, and they have been known to limit throughput in the mask shop.) These regressions have yielded no significant correlation between the dependent and the independent variables, suggesting either that economies of scale do not apply to photomask manufacturing (in contrast to semiconductor manufacturing) or that some mask shops are not able to take advantage of economies of scale.

We speculate that decentralized photomask manufacturing, which is driven by the needs of chipmakers, constitutes the primary factor that limits economies of scale. According to [27], "many high tech industries are characterized by shrinking product lifecycles, [as well as] increasingly expensive production equipment and up-front cost. … These forces pressure organizations to cut not only their development times (time-to-market), but also the time it takes to reach full production volume (time-to-volume), in order to meet their financial goals for the product (time-to-payback).” Recent studies suggest that this observation characterizes semiconductor manufacturing: it is in the interest of chipmakers to begin the yield learning process as early as possible and to ramp to volume production as rapidly as possible [16, 28, 29]. Chipmakers consequently demand that photomasks are produced on short notice and arrive in a very timely manner. A manager in charge of mask procurement for an ASIC-supplier articulates this need.

> *“Masks need to be ready and available when a prototype lot comes to the lithography station. If we discover a mask defect in the last moment, then the mask has to be repaired within a few hours. If we find a design error, then a new mask has to be made rapidly. In such situations a 15-hour trip across the Pacific is unacceptable. … We insist that our mask suppliers have local capabilities.”*

Many photomask manufacturers consequently practice decentralized photomask manufacturing to provide rapid turn around for their customers at the expense of underutilizing big ticket items such as PG-tools [17] and of being unable to achieve economies of scale [19]. Yet a recent study concludes that economies of scale are essential to profitable mask making [20], suggesting that decentralized photomask manufacturing is an unsustainable practice unless photomask manufacturers “operate on a scale large enough to make rapid technology turnover and manufacturing redundancy affordable. [30]” Our experts suggest that the price of a mask will influence the debate concerning turnover and scale. A senior manager at a merchant mask shop comments.

> *“When a customer is given a choice between an additional $50k on the price of a mask and a 24-hour trip across the Pacific [for the mask], the customer will*

> *choose the trip across the Pacific. … Time for delivery can be planned in advance. If the customer tells us that the mask is needed at a certain time, then we can plan to deliver on time. … It is much more difficult to respond to a request for a repair that needs to be done immediately.”*

A senior lithographer who is familiar with the practices of many mask shops has suggested a possible way out of this dilemma.

> *“The need for repairing masks on demand is more pressing than the need to write new reticles on demand. … We should look into a business model which allows for local mask repair on short notice but tolerates centralized mask making. This should be feasible if circuit designers improve the reliability of their design processes.”*

4.4 Advancing Technology

The technology index for the most advanced participant was more than 3.5 times as high as that of the least advanced participant, suggesting that some mask makers push the technological edge significantly more than others. Table 3 displays a correlation between the technology index and the number of engineers per plates shipped, a proxy for the level of investment in engineering. Table 4 exhibits a correlation between the technology index and the number of (non-sellable) engineering plates per plate shipped, a proxy for investment in experimentation capacity. These results suggest making masks that print small geometries requires a disproportionate engineering effort, which manifests itself in a high level of experimentation activity that consumes engineering plates. By contrast, we observed no significant correlation between the technology index and the fraction of the mask shop containing a Class 1 clean room, indicating that airborne micro-contaminants may not be a major factor that limits the production of state-of-the-art photomasks.

Table 3. Technology Index vs. Number of Engineers per Plate Shipped

Regression Statistics	R^2	AR^2	SE	n
	0.915	0.887	0.101	5
ANOVA	Coef.	SE	t-stat	1-p
Intercept ‘b’	0.332	0.0535	6.20	0.992
Slope ‘a’	0.677	0.119	5.70	0.989

Table 4. Technology Index vs. Number of Engineering Plates/Number of Plates Shipped

Regression Statistics	R^2	AR^2	SE	n
	0.949	0.899	0.122	3
ANOVA	Coef.	SE	t-stat	1-p
Intercept ‘b’	0.315	0.092	3.44	0.820
Slope ‘a’	0.684	0.158	4.33	0.856

Table 5. Technology Index vs. Number of Plates Shipped (number of plates shipped>20,000/year)

Regression Statistics	R^2	AR^2	SE	n
	0.719	0.625	0.127	5
ANOVA	Coef.	SE	t-stat	1-p
Intercept ‘b’	0.439	0.122	3.59	0.963
Slope ‘a’	0.579	0.119	2.77	0.931

Table 5 illustrates that a fairly strong, direct correlation between the technology index and the number of plates produced per year exists for participants that produce more than 20,000 product plates per year. This finding implies that large photomask manufacturers are better able to take advantage of economies of scale, when it comes to financing tools and innovations that are required to provide customers with masks of the next technology node. The correlation between the technology index and the number of plates shipped is no longer significant when mask shops that produce fewer than 10,000 plates per year are added to the sample. Very small photomask manufacturers may be engaging in different strategies from the ones that larger photomask manufacturers are pursuing.

5. SUMMARY

Our survey-based empirical study of photomask manufacturing productivity has led to a few significant conclusions. Firstly, the wide variation in productivity indicators from company to company suggests that all participants may have significant cost-reduction opportunities within their operation. Secondly, capital is underutilized even among the most productive photomask manufacturers. These results strongly suggests that detailed follow-on studies of the cost structure, the management structure and the procedures within mask shops will result in reduced mask costs. Thirdly, high downtime of pattern-generation tools is limiting productivity. In addition, producing smaller feature sizes is correlated to an investment in engineering and experimentation capacity. It could not be confirmed that photomask manufacturers are taking advantage of economies of scale. Given that scale has been established as a key factor contributing to the profitability of photomask manufacturers [20], this finding suggests that the profitability outlook for many manufacturers is precarious at best.

The survey approach in this paper is limited in a variety of ways. Firstly, it provides no data on time- or node-lifecycle-dependent cost issues (e.g., yield improvement rates, equipment purchase timing relative to node introduction, etc.). Secondly, it contains only questions that only yield numerical answers, thus not allowing access to important best practices and methodology information. Thirdly, the current survey format provides no information on organization, procedures, training, geographical variations, or merchant-versus-captive management differences. Some external survey information on such issues is available from external sources, but not in a comprehensive form. Obtaining information of this kind would require an approach much like that of the CSM study carried out for the semiconductor industry by UC Berkeley in the 1990’s [31, 32], involving site visits and a one-time survey for mask making that addresses the aforementioned issues. This approach should reveal photomask industry trends, best practices and strategies for ameliorating photomask cost escalation.

Finally, the authors recommend that this survey be repeated on an annual basis as a regular feature of Sematech's mask industry assessment effort (e.g., [12-15]) and perhaps be expanded. Regular answers to productivity-oriented questions are likely to provide the important relative measures of cost-related performance, which are considered to be so important to guiding management priorities and actions in mask shops. Larger sample sizes, which would result from full participation by all photomask manufacturers, would permit statistical identification and multivariate analysis of the underlying factors that drive photomask manufacturing. However, the broad participation of the respondents in 2005, as well as their willingness to answer these new and highly proprietary questions in the survey, indicates a strong interest in productivity-related aspects of the mask-making business within the mask-making community.

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TABLE CAPTIONS

Table 1. Range Ratios for Selected Variables

Table 2. Yield (Attenuated PSM) vs. Number of FTE Engineering Employees

Table 3. Technology Index vs. Number of Engineers per Plate Shipped

Table 4. Technology Index vs. Number of Engineering Plates/Number of Plates Shipped

Table 5. Technology Index vs. Number of Plates Shipped (number of plates shipped > 20,000/year)

Table A1. Normalized survey results pertaining to operating cost factors

Table A2. Normalized survey results pertaining to masks shipped per equipment.

Table A3. Normalized survey results pertaining to engineering (non-production) plates

Table A4. Normalized survey results pertaining to scheduled downtime

Table A5 -- Normalized survey results pertaining to unscheduled downtime

APPENDIX

Table A1. Normalized survey results pertaining to operating cost factors

			n	avg.
6.0	**Operating Cost Factors**			
6.1	Masks shipped per square foot of total clean room space		5	1.33
6.1a	Masks shipped per square foot of Class 1 clean room space		5	6.29
	6.1.1	Fraction of mask shop space that is Class 1	5	0.43
	6.1.2	Fraction of mask shop space that is Class 10	5	0.28
	6.1.3	Fraction of mask shop space that is Class 100	5	0.30
6.2	Masks shipped per FTE employee		5	140.14
6.3	Masks shipped per non-exempt FTE empoyee directly involved in manufacturing		5	577.00
6.4	Masks shipped per exempt non-engineering FTE employee directly involved in manufacturing		4	325.07
6.5	Masks shipped per engineering FTE employee directly involved in manufacturing		5	1069.06
	6.5.1	Number of process control engineers per 10,000 masks shipped	4	5.92
	6.5.2	Number of yield engineers per 10,000 masks shipped	4	5.58
	6.5.3	Number of equipment maintenance/installation engineers per 10,000 masks shipped	4	19.54
	6.5.4	Number of R&D, new process development engineers per 10,000 masks shipped	4	18.82
	6.5.5	Number of data processing engineers per 10,000 masks shipped	4	5.28
	6.5.6	Number of sustaining engineers per 10,000 masks shipped	4	20.08

Table A2. Normalized survey results pertaining to masks shipped per equipment.

			n	avg.
7.1	Average number of masks shipped per Pattern Generator			
	7.1.1	Laser PG's	5	1099
	7.1.2	Vector shaped e-beam PG's <50 kV	3	522
	7.1.3	Vector shaped e-beam PG's > = 50 kV	4	566
	7.1.4	Raster or vector spot e-beam PG's <50 kV	3	212
	7.1.5	Raster or vector spot e-beam PG's > = 50 kV	5	0
	7.1.6	Other PG's	1	229
7.2	Average number of shipped masks measured per CD Measurement Tool			
	7.2.1	Optical MUV tools	5	1197
	7.2.2	Optical DUV tools	4	152
	7.2.3	SEM CD tools	3	195
	7.2.4	Other CD tools	1	2591
7.3	Average number of shipped masks inspected per Defect Inspection Tool			
	7.3.1	Die:die inspection tools	5	934
	7.3.2	Die:database inspection tools	5	1482
7.4	Average number of shipped masks repaired per Defect Repair Tool			
	7.4.1	Laser repair tools	5	744
	7.4.2	FIB repair tools	5	204
	7.4.3	Mechanical (nano-shaping) tools	2	44

Table A3. Normalized survey results pertaining to engineering (non-production) plates

			n	avg.
7.5	Fraction of plates printed that are engineering (non-production) plates		3	12.6%
	(Next 6 lines should add to 100%)			
	7.5.1	% printed on Laser PG's	6	29.5%
	7.5.2	% printed on Vector shaped e-beam PG's at your facility: <50 kV	3	7.0%
	7.5.3	% printed on Vector shaped e-beam PG's at your facility: > = 50 kV	5	71.6%
	7.5.4	% printed on raster or vector spot e-beam PG's at your facility: <50 kV	3	14.7%
	7.5.5	% printed on raster or vector spot e-beam PG's at your facility: > = 50 kV	6	0.0%
	7.5.6	% printed on other PG's at your facility	6	0.0%
7.6	Fraction of plates CD measured that are engineering (non-production) plates		2	13.7%
	(Next 4 lines should add to 100%)			
	7.6.1	% measured on optical CD measurement MUV tools at your facility	3	60.4%
	7.6.2	% measured on optical CD measurement DUV tools at your facility	2	18.0%
	7.6.3	% measured on SEM CD measurement tools at your facility	4	45.7%
	7.6.4	% measured on other CD measurement tools at your facility	4	0.0%
7.7	Fraction of plates inspected by Defect Inspection Tools that are engineering plates		1	14.0%
	(Next 2 lines should add to 100%)			
	7.7.1	% measured on die:die inspection tools at your facility	5	62.9%
	7.7.2	% measured on die:database inspection tools at your facility	6	47.6%
7.8	Fraction of plates altered using Defect Repair Tools that are engineering plates		2	1.4%
	(Next 3 lines should add to 100%)			
	7.8.1	% altered using laser repair tools at your facility	3	34.9%
	7.8.2	% altered using FIB repair tools at your facility	4	67.3%
	7.8.3	% altered using mechanical (nano-shaping) tools at your facility	3	19.7%

Table A4. Normalized survey results pertaining to scheduled downtime

			n	avg.
7.9	Total scheduled down time of Pattern Generators of a given type (percent)			
	7.9.1	Laser PG's	4	6.0%
	7.9.2	Vector shaped e-beam PG's: <50 kV	3	5.0%
	7.9.3	Vector shaped e-beam PG's: > = 50 kV	4	7.1%
	7.9.4	Raster or vector spot e-beam PG's: <50 kV	1	2.0%
	7.9.5	Raster or vector spot e-beam PG's at your facility: > = 50 kV	na	N/A
	7.9.6	Other pattern generators	1	2.0%
7.10	Total scheduled down time of all CD Measurement Tools of a given type (percent)			
	7.10.1	Optical CD measurement MUV tools	2	1.2%
	7.10.2	Optical CD measurement DUV tools	2	0.9%
	7.10.3	SEM CD measurement tools	3	1.9%
	7.10.4	Other CD measurement tools	1	2.0%
7.11	Total scheduled down time of all Defect Inspection Tools of a given type (percent)			
	7.11.1	Die:die inspection tools	4	2.6%
	7.11.2	Die:database inspection tools	3	3.7%
7.12	Total scheduled down time of all Defect Repair Tools of a given type (percent)			
	7.12.1	Laser repair tools	4	2.0%
	7.12.2	FIB repair tools	4	3.0%
	7.12.3	Mechanical (nano-shaping) tools	2	2.0%

Table A5 -- Normalized survey results pertaining to unscheduled downtime

		n	avg.
7.13	Total unscheduled down time of Pattern Generators of a given type (percent)		
7.13.1	Laser PG's	3	4.0%
7.13.2	Vector shaped e-beam PG's: <50 kV	2	8.9%
7.13.3	Vector shaped e-beam PG's: > = 50 kV	4	5.1%
7.13.4	Raster or vector spot e-beam PG's: <50 kV	1	1.0%
7.13.5	Raster or vector spot e-beam PG's at your facility: > = 50 kV	0	n/a
7.13.6	Other pattern generators	1	1.0%
7.14	Total unscheduled down time of all CD Measurement Tools of a given type (percent)		
7.14.1	Optical CD measurement MUV tools	2	0.8%
7.14.2	Optical CD measurement DUV tools	2	0.8%
7.14.3	SEM CD measurement tools	2	6.2%
7.14.4	Other CD measurement tools	1	10.0%
7.15	Total unscheduled down time of all Defect Inspection Tools of a given type (percent)		
7.15.1	Die:die inspection tools	4	2.8%
7.15.2	Die:database inspection tools	4	3.0%
7.16	Total unscheduled down time of all Defect Repair Tools of a given type (percent)		
7.16.1	Laser repair tools	4	2.5%
7.16.2	FIB repair tools	4	4.6%
7.16.3	Mechanical (nano-shaping) tools	2	6.0%

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