Shop-Floor Scheduling of Semiconductor Wafer Fabs: Exploring the Influence of Technology, Market, and Performance Objectives

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***Abstract*—Shop-floor control has long been recognized as an important tool in improving manufacturing performance, an issue of great importance in the highly competitive semiconductor industry. Despite theoretical evidence of the benefits of certain kinds of scheduling policies, a wide disparity in shop-floor control practices exists in the industry. To better understand why such differences exist, we analyze an array of technology, market, and performance objective variables from 28 semiconductor wafer fabs. Using an ordinal logit model, we find that custom chip makers and fabs that place high emphasis on delivery performance are more likely to place high emphasis on lot dispatching and shop-floor control. Make-to-stock fabs producing mature products are less likely to place high emphasis on scheduling. For practitioners, the results can help direct management efforts by indicating which fabs will—and which will not—benefit from emphasis on scheduling. For scholars, the results suggest fruitful areas for future production scheduling research.**

***Index Terms*—Dispatching, production scheduling, shop-floor control.**

I. Introduction

THE SEMICONDUCTOR industry is characterized by high capital costs, rapidly changing technology, and fierce competition. As a result, semiconductor wafer fabrication facilities (*fabs*) face increasing pressure to reduce costs, increase quality, and improve delivery performance.

Shop-floor scheduling has long been recognized as an important tool in improving manufacturing performance, and there has been a torrent of research in the last 10–15 years aimed at developing effective scheduling policies for semiconductor production. The majority of this research has been concerned with theory development, e.g., the “best” way to improve a particular performance measure such as cycle time. Other research reports on the development and/or implementation of scheduling policies at specific fabs. Despite the seemingly obvious benefits provided by certain policies and approaches, there is a wide disparity in the shop-floor control practices between fabs. Some fabs employ highly sophisticated systems and dispatching rules while others have made minimal efforts. How can these differences be explained?

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The purpose of this paper is to help bridge the gap between the theory and practice of scheduling semiconductor wafer fabrication by understanding the links between fab characteristics and their emphasis on shop-floor control policies. Put differently, while previous research has focused on the question of *how* to schedule, we seek to understand *why* some fabs emphasize scheduling and others do not.

Through qualitative and quantitative analysis of data from 28 factories, we show that custom chip makers and fabs that place high emphasis on delivery performance are more likely to place high emphasis on lot dispatching and shop-floor control. Make-to-stock fabs producing mature products are less likely to place high emphasis on scheduling. For practitioners, this paper provides ideas and guidance as to which system characteristics matter in terms of shop-floor control. For scholars, this paper suggests directions for future research, helping to identify the kinds of production scheduling models that will be of interest and value to practitioners.

The remainder of the paper is organized as follows. We first review the existing literature related to production scheduling in the semiconductor industry. Next, we present data regarding the technology, market, and performance objective characteristics of different fabs and explain how the data will be analyzed. Results are then presented and discussed. In Section V, we discuss conclusions and the implications for researchers and practitioners.

II. Background

A. Literature Review

A great deal of research has been done on production control in the semiconductor industry, and rather than attempt a comprehensive review, here we simply seek to provide an overview of the research landscape. Readers are referred to Uzsoy *et al.* [1] for a review of more than 60 papers on scheduling in the semiconductor industry. We divide the relevant production control literature into two categories: theory development and application.

Theory development research typically involves using analytical models to develop production control rules that optimize a particular performance measure, e.g., minimize mean cycle time. Computer simulations are used to test the proposed policies against other approaches. Generally, research on production control involves two types of decisions: *input control*, the decision of when to release new work into the system, and *scheduling*, the decision of which job to process next at a particular work station. (The terms *sequencing* and *dispatching* are, for our purposes, synonymous with *scheduling*). Early research on these topics concluded that input control had a bigger impact on flow time measures than scheduling [2], [3]. This conclusion led some researchers to focus exclusively on input control, e.g., [4] and [5]. Other researchers focused exclusively on scheduling, e.g., [6] and [7].

While researchers continue to debate which aspect of production control is the most important and which policies are theoretically optimal, it is often not clear if and how the lessons from the models could be applied in practice. Many models are of single-product systems and require a great deal of information to be implemented. Most of the research emphasizes cycle time measures, but is this the most important performance measure for all, or even most, fabs?

The second category of production control literature focuses on the application of specific policies. This type of research includes surveys of current practices (such as [8] and [9]) and descriptions of "success stories" at individual fabs (such as [10]–[12]). While this research demonstrates the value of increased emphasis on production control for particular fabs, it is not clear how general the results are. Would all fabs benefit from the implementation of such systems?

In spite of these questions about production control, fabs continue to operate and fab managers continue to make decisions. Some place high emphasis on scheduling while others do not. Is this a case of managers failing to heed important advice, researchers answering questions that are not relevant, or some combination of the two?

Another related stream of research attempts to explore empirically the links between firm characteristics, manufacturing practices, and various performance measures. For example, many papers such as [13] report on total quality management programs and their effect on firm performance. Other papers such as [14] study the relationship between just-in-time production control and manufacturing performance. Other studies report on manufacturing results specifically from the semiconductor industry [15]. These papers differ from ours in two important ways. First, these studies are primarily concerned with firm-level financial performance such as revenues and stock prices, whereas our study in concerned with factory-level characteristics. Second, these studies are designed to link practices with outcomes, whereas our study emphasizes the practice itself. Rather than predict or describe what the result of a particular practice will be, we predict when a fab is likely to engage in a practice.

B. CSM Study

The motivation and data for this paper came from the author's work with the Competitive Semiconductor Manufacturing (CSM) Survey, a multiyear research project conducted by the University of California, Berkeley, under the sponsorship of the Alfred P. Sloan Foundation. The purpose of the survey is to measure manufacturing performance and investigate the underlying determinants of performance in the semiconductor industry. The survey includes wafer fabs in the U.S., Asia, and Europe. Each participant completes a 50-page questionnaire that provides detailed information about their operations—types of equipment used, number of employees, product specifications, etc. A team of researchers visits each facility to follow up on the data from the questionnaire and gather qualitative data on operational practices. By interviewing a cross section of fab personnel, the team is able to collect information about fab objectives and strategy, improvement practices, information technology, scheduling practices, etc. For more details about the project and findings, refer to [16].

III. Methodology

Previous research on scheduling semiconductor wafer fabs has focused on the question of *how* to schedule, and one can think of many situations where improved scheduling *should* theoretically make a difference in performance. But questions of relevance remain. Which fabs actually *do* care about scheduling and take actions to improve scheduling decisions? Put differently, what are the characteristics of fabs that are associated with strong emphasis on shop-floor control? And how well do the models presented in the literature match up with the characteristics of "real-world" fabs? To answer these questions, we need three things: descriptive data from a cross section of fabs, a way to measure scheduling emphasis, and a method to explore the relationship between the former and the latter. Each of these items is discussed below.

A. Descriptive Variables

Descriptive data on 28 fabs, collected through the CSM Survey, were compiled and divided into six categories. Each category and variable is discussed below. Some of the 18 descriptive variables have numerical values by definition, while others do not; but all of the variables must be translated into numerical values to perform statistical analyses. Where applicable, the numerical values used are indicated in parentheses. The complete dataset is presented in Tables IV and V in the Appendix.

Facility Variables

- *Facility Size*: the area of the fab's clean-room space. Fabs with more than 60 000 square feet are coded as "Large" $(= 2)$; fabs with less than 20 000 square feet are coded as "Small" $(= 0)$; other fabs are coded as "Med." $(= 1)$.
- *Facility Class*: the cleanliness level of the fab's clean room. A value of class x indicates that the facility has no more than 10^x particles of size 0.5 μm or larger per cubic foot of clean-room space.
- *Facility Age*: the age of the fab. Fabs constructed before 1985 are "Old" $(= 2)$; fabs constructed between 1985 and 1990 are "Mid." $(= 1)$; fabs constructed after 1990 are "New" $(= 0)$.

Process Variables

- *Process Type*: the primary process technology type employed by the fab. Possible values are bipolar $(= 1)$ and complementary metal–oxide–silicon (CMOS $=$ 0), the two most prevalent process technology types in the industry.
- *Wafer Size*: the diameter, in inches, of the wafers produced by the fab.

- *Process Age*: the age, in months, of the fab's highest-volume process.
- *Automation Level*: the level of automation in the factory. We consider four areas: automated material handling, robotic linking of photolithography cells, automated recipe download, and automated data entry. For each category, a fab is given a score of 1 if they have installed this type of automation and a score of 0 otherwise. The automation variable listed is the sum of these scores, where "None" indicates of score of 0, "Low" indicates a score of 1, "Med." indicates a score of 2, "High" indicates a score of 3, and "V.High" indicates a score of 4. (The respective numerical values are used in the statistical analyses that follow).

Product Variables

- *Product Type*: refers to whether the fab primarily produces logic devices $(= 0)$, memory chips $(= 2)$, or both $(= 1)$.
- *Minimum Feature Size*: the minimum feature size, or linewidth, of devices from the fab's highest-volume process flow, measured in microns.
- *Die Size*: the area, measured in square centimeters, of a representative die type from the fab's highest-volume process flow.

Volume/Capacity Variables

- *Wafer Starts*: the number of wafers per week started in production, averaged over the last year for which data were collected.
- *Number of Flows*: the total number of process flows actively being produced by the fab.
- *Number of Products*: the total number of different product types actively produced by the fab. It is possible to produce many products from a single process flow.

Market Variables

- *ASIC Production*: refers to whether or not the fab produces application-specific integrated circuits (ASICs), i.e., customized products. ASIC fabs are indicated by "Yes" $(= 1)$, and non-ASIC fabs are indicated by "No" $(= 0)$.
- *Captive Fab*: refers to whether or not the fab is dedicated to making chips for a parent company that will be used in end products such as computers, answering machines, etc. Captive fabs are indicated by "Yes" $(= 1)$, and noncaptive fabs are indicated by "No" $(= 0)$.
- *Make-to-Order*: refers to whether or not the fab primarily produce to order (i.e., for a specific customer) or to stock (i.e., for inventory). Make-to-order fabs are indicated by "Yes" $(= 1)$, and make-to-stock fabs are indicated by "No" $(= 0)$.

Performance Objective Variables

- *Cycle Time*: refers to whether or not the fab considers cycle time, the total time it takes for a fab to manufacture a product, one of its primary performance metrics. A value of "Yes" $(= 1)$ or "No" $(= 0)$ was assigned based on the responses given by fab personnel during the on-site interviews conducted as part of the CSM Survey.
- *On-Time Delivery*: refers to whether or not the fab considers on-time delivery one of its primary performance metrics. On-time delivery is usually defined as the percentage of items scheduled for delivery (or production) during a certain period of time, divided by the actual delivery (or production) quantity during that period. A value of "Yes" $(= 1)$ or "No" $(= 0)$ was assigned based on the responses given by fab personnel during the on-site interviews conducted as part of the CSM Survey.

The underlying idea is that differences between fabs with respect to these variables will explain why fabs approach scheduling decisions differently.

B. Measuring Scheduling Emphasis

How does one measure "emphasis" on scheduling? Presumably fabs do what is in their best interests, but it seems that simply asking fabs to rate themselves on scheduling emphasis may not accurately reflect their true behavior. For example, we came across many fabs in our survey that expended a great deal of effort on lot dispatching decisions. But several of these fabs did not approach such decisions in a systematic way. Rather, they seemed to be in a "fire-fighting" mode, expediting certain lots that had fallen behind schedule.

On the other hand, we discovered many fabs with highly sophisticated shop-floor control systems that seemed to have little impact on the actual operations of the fab. We listened as industrial engineers and information systems experts enthusiastically described their fab's state-of-the-art dispatching system. One fab used an expert system to determine lot priorities. Several engineers described complex algorithms that determine lot priorities as a function of average cycle time, machine availability, equipment setups, due dates, etc. But during fab tours, we found that the reality of the shop floor did not match the engineers' description. In one fab, the expert system had been turned off—low volume levels had rendered it impotent. In another fab, operators often ignored the dispatching priorities suggested by the shop-floor control system, so they could reduce the number of equipment setups.

To arrive at a more objective measure of scheduling emphasis that accurately reflects fab behavior, we construct a variable that is composed of the two underlying dimensions discussed above: effort and sophistication. The goal is to identify fabs that put forth much effort on scheduling and do so in a systematic, effective way.

Effort is defined as a binary, qualitative variable. Each fab receives a rating of high or low effort based on information from our fab tour and on-site interviews with production control personnel, operators, supervisors, and engineers. Thus, the assessment of effort is based on answers to scheduling-specific questions as well as on what is actually observed in practice. Returning to the example mentioned above, if operators indicate that scheduling decisions receive little attention, then the fab will receive a rating of low effort, even if later engineers report the development of an expert system to aid in dispatching. In contrast, if operators and supervisors tell a consistent story about expending much effort in determining lot priorities and accommodating changing lot priorities, then the fab will receive a rating of high effort, even if the effort does not seem to be particularly effective or well organized.

Sophistication is judged by three criteria. First, does the fab have a real-time, computerized lot-tracking/dispatching system? Second, are dispatching priorities lot specific? Third, is dispatching mostly anticipative or reactive? Rushing “express” lots through the system to make up for forecast errors does not fit our definition of sophisticated dispatching. Fabs that can answer affirmatively to any two of the three questions are given a rating of high sophistication. Otherwise, the fab is given a rating of low sophistication.

Scheduling emphasis is a three-level variable defined as a combination of effort and sophistication. Fabs that are rated high on effort and high on sophistication are rated high on scheduling emphasis. Fabs that are rated low on effort and low on sophistication are rated low on scheduling emphasis. All other fabs are rated medium on scheduling emphasis. In our sample of 28 fabs, nine were rated “Low” $(= 0)$, twelve were rated “Med.” $(= 1)$, and seven were rated “High” $(= 2)$. The responses for each fab are reported in Table V.

C. Ordinal Logit Model

Now that we have identified the fab characteristics and measured emphasis on scheduling, we need a way to explore the central question of the paper: How are these two things related? A simple linear regression model might appear to be a useful way to explore this relationship, but research has demonstrated that such models are not appropriate for discrete response variables such as scheduling emphasis. Many of the fundamental assumption of the linear regression model are not satisfied, and it is possible to have predicted values that are infeasible (i.e., above the highest category or below the lowest category). Thus, we use a closely-related model called an ordinal logit model (OLM), one of the most common methods to analyze ordinal response variables. For a complete description of OLMs, refer to [17].

Like a linear regression model, the basic OLM expresses the response variable y^* as a function of some predictor variables, x_k, where $k = 1, 2, \ldots, K$, and some randomness, ε

$$y^* = \sum_k \beta_k x_k + \varepsilon.$$

However, unlike a standard linear regression model, the term ε has a logistic distribution. In addition, the “true” response, y^*, cannot be directly observed; it can be thought of as the underlying tendency of an observed phenomenon. For example, the utility or value a fab places on shop-floor control cannot be directly measured or observed, but we *can* observe whether they place high, medium, or low emphasis on scheduling. Thus, what is actually observed is

$$y = j \text{ if } \tau_{j-1} \le y^* < \tau_j$$

for responses $j = 1, 2, \ldots, J$. The τs are thresholds or cutpoints that separate adjacent categories. The probability that the observed y falls into category j can be expressed as

$$\Pr\{y=j\} = L\left(\tau_j - \sum_k \beta_k x_k\right) - L\left(\tau_{j-1} - \sum_k \beta_k x_k\right) \quad (1)$$

where $L(\cdot)$ denotes the logistic distribution function. The goal of the OLM is to find τs and βs that best describe the relationship between the observed explanatory variables and the observed response variable.

D. Factor Analysis

Most multivariate data analysis techniques require large sample sizes to be valid. To help mitigate the fact that we have a relatively small sample, we make use of factor analysis. This technique is commonly used to reduce the number of explanatory variables, thereby improving the ability to perform statistical analyses. The goal is to determine the underlying structure of the data, allowing one to describe the original set of variables using a reduced set of factors. For a complete description of factor analysis, refer to [18]. Suppose that we observe a vector of responses, $\mathbf{x}$. Factor analysis attempts to find a set of common factors and a set of unique factors such that original responses can be described as a linear combination of the two. The basic model is

$$\mathbf{x} = \mathbf{\Lambda f} + \mathbf{e} \quad (2)$$

where $\mathbf{f}$ is a vector of common factors, $\mathbf{e}$ is a vector of unique factors, and $\mathbf{\Lambda}$ is a matrix of constants known as *factor loadings*.

Performing factor analysis involves three steps: extracting the factors, deciding how many factors to retain, and interpreting the factors. If one observed n variables, then it would be straightforward to construct a new set of n factors that are simply linear combinations of the original variables. The trick is to find a reduced set of factors that still adequately accounts for the variation in the original data set. We chose the maximum likelihood extraction method because it does not depend on the scale of measurement (as some other methods do), and it allows us to statistically test if the number of factors retained is adequate. The results of the extraction and interpretation of the factors follows.

IV. RESULTS

A. Factor Analysis Results

Using the factory analysis technique described above, four factors were extracted from the original set of 18 descriptive fab variables. Are four factors sufficient to describe the variation in the original set of variables? This question can be tested statistically: the result is an asymptotic chi-square statistic of 75.5 (87 df), which has a p value of 0.8. Thus, we can reject the null hypothesis that more factors are needed and conclude that the four-factor model is adequate.

Table I reports the factor loadings, i.e., the $\mathbf{\Lambda}$ matrix from (2), and the cumulative variance explained by the factors. By examining the loadings, we can determine which of the original variables are most closely associated with the factors—a higher loading indicates a stronger relationship. Applying the standard guidelines described in [18], we interpret each of the factors.

Factor 1 has high positive loadings on facility age and minimum feature size. It has high negative loadings on process type, wafer size, and product type. It has moderate positive loadings on facility class and process age and has a moderate negative loading on automation level. Referring to the variable

TABLE I
FACTOR ANALYSIS RESULTS: FACTOR LOADINGS

Variable	Factor 1 (*Low Tech.*)	Factor 2 (*Make-to-Order*)	Factor 3 (*New Tech.*)	Factor 4 (*High Vol.*)
Facility Size	−0.13	−0.22	0.04	0.58
Facility Class	0.49	−0.33	−0.04	0.18
Facility Age	0.89	−0.01	−0.06	−0.04
Process Type	−0.57	0.35	0.53	0.03
Wafer Size	−0.71	0.17	0.32	0.03
Process Age	0.43	0.16	−0.01	−0.05
Automation Level	−0.42	−0.04	0.42	0.44
Product Type	−0.56	−0.15	−0.11	0.42
Min. Feature Size	0.52	−0.30	−0.32	−0.08
Die Size	−0.12	0.00	0.99	−0.09
Wafer Starts	−0.03	0.01	−0.12	0.93
Number of Flows	0.12	0.29	0.09	0.49
Number of Products	0.37	0.41	−0.04	0.06
ASIC Production	0.11	0.56	0.17	−0.20
Captive	0.08	−0.25	0.47	−0.01
Make-to-Order	−0.17	0.85	0.01	0.05
Cycle Time Goals	0.16	0.23	0.01	0.00
On-Time Deliv. Goals	−0.12	0.54	−0.13	−0.19
Cumulative variance	0.36	0.53	0.68	0.80

TABLE II
ESTIMATED COEFFICIENTS FOR SCHEDULING EMPHASIS OLMs

	Model 1		Model 2	
Variables	Coefficient	Std. Error	Coefficient	Std. Error
Low Technology	0.23	0.44	—	—
Make-to-Order	1.68**	0.56	1.63**	0.55
New Technology	0.69*	0.40	0.66*	0.40
High Volume	0.54	0.45	—	—
Cutpoint 1	−1.25	0.52	−1.18	0.51
Cutpoint 2	1.58	0.58	1.54	0.56
Log likelihood	−22.48		−23.35	
Chi-square	15.21**		13.48**	

** $p < 0.01$.
* $p < 0.1$.

definitions in Section III, we see that high-class old fabs with low levels of automation that produce logic devices with large linewidths on small wafers using mature, bipolar process technology will have high Factor 1 scores. Thus, we label this factor as *Low Technology*. Older fabs using older process and product technologies will have higher scores, while newer fabs using newer process and product technologies will have lower scores.

Factor 2 has high positive loadings on ASIC production, make-to-order, and on-time delivery and a moderate positive loading on number of products. Fabs that manufacture customized products, produce to order rather than to stock, and emphasize on-time delivery performance will have high Factor 2 scores. Fabs that make commodity products, produce to stock, and do not emphasize on-time delivery performance will have low Factor 2 scores. Thus, we label this factor as *Make-to-Order*.

Factor 3 is dominated by the high positive loading on die size and to a lesser degree by the positive loading on process type. There are moderate positive loadings on automation level and captive. Referring to the variable definitions in Section III, we see that fabs that produce larger chips using CMOS process technology will have high Factor 3 scores. Most new processes are CMOS, and new products tend to be produced on larger chips (and later shrunk as the process matures). We label this factor as *New Technology*.

Factor 4 has high positive loadings on facility size and wafer starts and has moderate positive loadings on automation level, product type, and number of flows. Large, high-volume fabs that have many process flows will have high Factor 4 scores. We label this factor as *High Volume*.

B. OLM Results

The OLM model described previously can now be used explore the relationship between fab characteristics and scheduling emphasis. The original array of 18 descriptive variables has been reduced to four factors for each of the 28 fabs in the sample. The four factors are the predictor variables, and scheduling emphasis is the response variable in (1). The results of two OLM models are reported in Table II. The initial model includes all four factors as predictor variables. The chi-square statistic

TABLE III
PREDICTED PROBABILITIES AS A FUNCTION OF FACTOR SCORES

	Factor Score[a]	Pr{Low}	Pr{Med.}	Pr{High}
Make-to-Order	−1.206	0.686	0.285	0.029
	−0.370	0.359	0.536	0.105
	0.466	0.126	0.561	0.313
	1.302	0.036	0.324	0.640
	2.139	0.009	0.117	0.874
	Total Change[b]	−0.677	−0.168	0.845
	S. D. Change[c]	−0.266	0.047	0.219
	Factor Score[a]	Pr{Low}	Pr{Med.}	Pr{High}
New Technology	−1.386	0.434	0.487	0.079
	−0.307	0.273	0.578	0.149
	0.772	0.155	0.582	0.263
	1.851	0.083	0.496	0.422
	2.931	0.042	0.360	0.598
	Total Change[b]	−0.392	−0.127	0.519
	S. D. Change[c]	−0.119	0.023	0.096

[a] *Factor Score*: values of each factor score, ranging from the minimum observed value to the maximum observed value.
[b] *Total Change*: the difference in predicted probability when the factor goes from its minimum to its maximum value, holding all other variables constant. Probabilities are computed using (1).
[c] *S. D. Change*: the difference in predicted probability for a one standard deviation change in the factor score, holding all other variables constant. The change is centered around the mean, i.e., from $(\bar{x}_k - s_k/2)$ to $(\bar{x}_k + s_k/2)$, where $\bar{x}_k$ is the mean and s_k is the standard error of the factor being changed. Probabilities are computed using (1).

refers to the test of the overall goodness of fit of the model, i.e., the hypothesis that all coefficients are zero. The large chi-square value indicates that we may reject this hypothesis: at least one coefficient is nonzero. However, we do not expect all of the factors to strongly influence scheduling emphasis. Furthermore, experts recommend a minimum sample size of 15 cases per predictor variable [19], so a two-variable model seems reasonable for our sample of 28 fabs.

Examining Table II reveals that *Make-to-Order* and *New Technology* are the only statistically significant variables in the four-factor model. The second OLM model, therefore, includes only these two factors. It is evident that the two-factor model is also highly significant, and *Make-to-Order* and *New Technology* are still significant. In fact, the coefficient estimates and standard errors for these terms are nearly identical to their values in the four-factor model.

Make-to-Order clearly has more influence than *New Technology*. The positive coefficient estimate indicates that increases in the *Make-to-Order* score are associated with an increase in scheduling emphasis. To determine the magnitude of the effect of a change in an independent variable, several approaches are possible. One approach is to use the coefficient estimate, $\hat{\beta}_k$, to compute the *odds ratio*, which is equal to $\exp(\hat{\beta}_k)$. The odds ratio indicates the change in the likelihood of a particular response given a one-unit change in a predictor variable, keeping all other variables the same. The odds ratio for *Make-to-Order* is approximately 5.1 $(= \exp[1.63])$. Holding *New Technology* constant, a one-unit increase in *Make-to-Order* makes it 5.1 times more likely that a fab will place high emphasis on scheduling rather than medium or low emphasis.

Further evidence of the influence of *Make-to-Order* is found in Table III, which reports the predicted probabilities for different values of this factor. The probabilities are computed using (1). Moving from the minimum observed value of *Make-to-Order* to its maximum observed value increases the predicted probability of high emphasis on scheduling by 0.845, decreases the predicted probability of medium emphasis by 0.168, and decreases the predicted probability of low emphasis by 0.677, with *New Technology* held constant at its mean. For an increase of one standard deviation in *Make-to-Order*, the predicted probability of high emphasis on scheduling increases by 0.219, the probability of medium emphasis increases by 0.047, and the probability of low emphasis decreases by 0.266, again with *New Technology* held constant at its mean.

These results are intuitively appealing. ASIC producers are generally making custom or semicustom products for specific customers. Fabs serving as foundries for other companies are often required to produce large volumes of standard products in a short period of time. These fabs will have high *Make-to-Order* scores and are, therefore, likely to be responsive to demand changes and to focus on delivery-related performance measures. Different dispatching policies can have a big impact in this situation. In contrast, a make-to-stock fab producing commodity products will not benefit as much from different dispatching policies: if there are few products, different sequencing rules will not have any leverage to change performance.

The results for *New Technology* are less significant. The odds ratio for *New Technology* is approximately 1.9. Holding *Make-to-Order* constant, a one-unit increase in *New Technology* makes it 1.9 times more likely that a fab will place high

TABLE IV
FACILITY, PROCESS, AND PRODUCT VARIABLES

Obs.	Facility Size	Facility Class	Facility Age	Process Type	Wafer Size	Process Age	Automation Level	Product Type	Min. Feat. Size	Die Size
1	Small	3	Old	Bipolar	4	27	None	Log.	3.0	0.15
2	Med.	2	Mid.	CMOS	6	50	Low	Log.	0.9	0.48
3	Med.	2	Old	Bipolar	4	45	Med.	Log.	2.0	0.03
4	Med.	0	Mid.	CMOS	6	64	High	Log.	0.9	1.31
5	Large	2	Mid.	CMOS	6	27	Med.	Both	0.7	0.83
6	Large	3	Old	CMOS	5	54	Med.	Log.	1.2	0.88
7	Large	2	Mid.	CMOS	6	23	V.High	Mem.	0.7	0.82
8	Large	1	Old	Bipolar	5	45	Low	Log.	10.0	0.21
9	Med.	0	New	CMOS	6	24	High	Both	0.8	0.45
10	Small	0	Old	CMOS	6	78	Med.	Log.	1.5	0.98
11	Med.	1	Mid.	CMOS	6	14	Med.	Log.	0.7	1.91
12	Small	2	Old	CMOS	5	23	Low	Log.	1.5	1.43
13	Med.	1	Mid.	CMOS	6	21	Low	Log.	1.0	0.74
14	Large	1	New	CMOS	6	12	V.High	Mem.	0.6	0.57
15	Small	0	Mid.	CMOS	6	30	Med.	Both	0.8	0.42
16	Small	2	Mid.	CMOS	5	12	None	Log.	1.2	0.36
17	Med.	1	Mid.	CMOS	5	30	Low	Log.	0.9	0.70
18	Small	1	Mid.	CMOS	5	36	Low	Both	1.5	0.52
19	Med.	1	Mid.	CMOS	6	27	Low	Both	0.8	0.23
20	Med.	1	New	CMOS	6	27	Low	Mem.	0.8	0.83
21	Med.	2	Old	Bipolar	5	48	None	Both	2.5	0.18
22	Med.	2	Mid.	CMOS	6	27	High	Both	0.8	0.82
23	Med.	0	Mid.	CMOS	6	5	Low	Log.	0.6	0.43
24	Med.	1	Mid.	CMOS	6	12	Med.	Mem.	0.8	0.53
25	Med.	1	Mid.	Bipolar	6	54	None	Log.	2.0	0.03
26	Med.	2	Old	Bipolar	4	34	None	Both	5.0	0.04
27	Med.	1	Old	CMOS	5	32	Low	Log.	1.2	0.31
28	Med.	0	Mid.	CMOS	6	37	Low	Mem.	0.7	0.49

Refer to Section III for variable descriptions.

emphasis on scheduling rather than medium or low emphasis. Predicted probabilities for different values of *New Technology* are reported in Table III. As *New Technology* moves from its minimum to its maximum observed value, the predicted probability of high emphasis on scheduling increases by 0.519, the predicted probability of medium emphasis decreases by 0.127, and the predicted probability of low emphasis decreases by 0.392, with *Make-to-Order* held constant at its mean. The predicted probabilities remain virtually unchanged for a one standard deviation increase in *New Technology*, holding *Make-to-Order* constant at its mean.

These results make sense in light of the significance of *Make-to-Order* discussed above. If one thinks about the typical product life cycle, it is logical that standardized products are more mature and are more likely to be made to stock than customized products. Leading-edge, customized products are more likely to be made to order. So fabs with high *Make-to-Order* scores are likely to be producing leading edge products. In other words, fabs with high *New Technology* scores will not necessarily place high emphasis on scheduling, but fabs that do place high emphasis on scheduling are more likely to have high *New Technology* scores.

It is important to note that the intent of this analysis is to reveal patterns or trends in the relationship between fab characteristics and scheduling practices. We may find individual fabs whose behavior does not match what we might expect or what the model predicts. This phenomenon may be the result of factors not included in the model, some of which may change over time. For example, scheduling will have less of an effect in environments where capacity utilization is very low, so a make-to-order fab experiencing low capacity utilization may choose not to place high emphasis on scheduling. In addition, a fab that is currently producing leading-edge memory products may eventually switch to logic products as the process and product technologies mature. So there is a connection between scheduling needs and the business model employed by the fab, and these needs may change over time.

Notwithstanding these issues, the model successfully explains much of the variation in scheduling practices between fabs, and the results are intuitively appealing. This solid, empirical link between fab characteristics and what they actually *do* in terms of scheduling gives a clear indication of how future research should be directed and what kinds of questions should be asked.

V. CONCLUSION

Despite the virtues of production control extolled by some researchers, there is a wide disparity among semiconductor wafer fabs in terms of emphasis on scheduling. We attempted

TABLE V
VOLUME, MARKET, AND SCHEDULING EMPHASIS VARIABLES

Obs.	Wafer Starts	Num. of Flows	Num. of Prods.	ASIC Production	Captive	Make-to-Order	Cycle Time Goals	On-Time Deliv. Goals	Scheduling Emphasis
1	1854	3	45	No	No	No	Yes	Yes	Med.
2	2798	4	50	No	No	No	No	No	Med.
3	11027	6	180	No	No	No	Yes	Yes	High
4	4538	1	5	No	No	No	No	No	Low
5	13883	55	320	No	No	Yes	Yes	No	High
6	5128	12	200	No	Yes	Yes	Yes	Yes	High
7	11364	5	12	No	No	No	No	No	Med.
8	2726	3	65	No	Yes	No	No	No	Low
9	7312	3	40	No	No	Yes	Yes	Yes	Med.
10	1879	7	600	Yes	No	Yes	Yes	Yes	High
11	590	2	13	No	Yes	No	Yes	No	Med.
12	301	2	10	No	Yes	No	Yes	No	Med.
13	3019	5	85	Yes	No	Yes	Yes	Yes	Med.
14	7191	3	15	No	No	No	Yes	No	Low
15	1814	9	85	No	No	Yes	Yes	Yes	Low
16	2512	10	400	No	No	No	No	No	Low
17	3929	5	150	Yes	No	Yes	No	Yes	High
18	821	4	61	No	No	Yes	Yes	Yes	Med.
19	6243	3	140	No	No	Yes	Yes	No	High
20	1214	2	3	No	Yes	No	No	Yes	Med.
21	2676	10	212	No	No	No	No	No	Low
22	10237	4	200	No	Yes	No	No	No	Med.
23	3100	3	15	No	No	Yes	No	Yes	High
24	5162	1	6	No	No	No	Yes	Yes	Med.
25	1900	5	200	No	No	No	Yes	No	Low
26	11088	5	130	No	No	No	Yes	No	Low
27	6601	3	50	No	No	No	Yes	No	Low
28	12507	7	10	No	Yes	Yes	No	Yes	Med.

Refer to Section III for variable descriptions.

to shed light on this phenomenon by posing the question: What are the characteristics of fabs that place high emphasis on shop-floor control? To answer this question, data regarding technology, market, and performance objective variables for 28 wafer fabs were collected through University of California Berkeley's CSM Survey. To help mitigate the effects of a small sample size, factor analysis was used to reduce 18 descriptive variables to four factors.

To measure emphasis on scheduling, a three-level, ordered response variable was constructed based on interviews with fab personnel and observation of practices. An OLM was used to explore the relationship between the fab characteristics (explanatory variables) and scheduling emphasis (response variable). We found that custom chip makers and fabs that place high emphasis on delivery performance are more likely to place high emphasis on lot dispatching and shop-floor control. Make-to-stock fabs producing mature products are less likely to place high emphasis on scheduling. Previous research has focused primarily on single-product systems and cycle time performance measures, indicating that theory development efforts may not be meeting the needs of real-world fabs.

For practitioners, these results can help direct management efforts by suggesting which fabs will—and which will not—benefit from increased attention to shop-floor scheduling. For scholars, these results indicate fruitful areas for future research, helping to bridge the gap between the previous theoretical models and the needs of fabs that would benefit most from the results. Specifically, more models of multiple-product systems are needed, and additional emphasis on due-date performance measures would be useful.

APPENDIX

See Tables IV and V.

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