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Identification and Prevention of Income Recognition Flushing: A Case Study of Chinese Semiconductor Listed Companies

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Keywords: Revenue Recognition Manipulation; Semiconductor Industry; Financial Fraud; Case Study; SMIC; Accounts Receivable Anomaly

Abstract: The global semiconductor industry faces unprecedented challenges from technological competition and geopolitical tensions, placing Chinese semiconductor companies under triple pressures of high R&D investment, lengthy capacity ramp-up cycles, and heavy capital expenditure burdens. These pressures create incentives for firms to manipulate revenue recognition, yet existing detection methods remain fragmented. This study addresses the gap by investigating revenue recognition manipulation in Chinese semiconductor listed companies through a dual-method approach combining case study and horizontal comparative analysis. Taking SMIC as a typical case, we analyze its revenue recognition patterns and capital expenditure dynamics from 2020 to 2024, revealing significant anomalies including revenue-cash flow deviations and abnormal accounts receivable growth. Key findings indicate that when the accounts receivable growth rate exceeds revenue growth by 15 percentage points, the probability of financial irregularities significantly increases. Furthermore, fourth-quarter revenue accounts for 38.7% of total annual revenue—substantially higher than the 26.4% average in other quarters—revealing distinct seasonal manipulation patterns. The study identifies dual driving forces behind manipulation: performance-based agreements requiring annual revenue growth above 30% and management stock incentives with revenue growth thresholds of ≥25%. Based on these findings, We found that the combined effect of performance agreements and incentive mechanisms significantly increases the risk of financial misstatements. This research contributes to fraud detection literature by providing industry-specific analytical frameworks for capital-intensive sectors and offers practical implications for auditors, regulators, and investors in identifying revenue recognition manipulation in high-tech industries.

1. Introduction

In recent years, the global semiconductor industry has entered a phase of accelerated transformation, shaped by both technological iteration and geopolitical tensions. According to IC Insights, the global semiconductor market reached approximately $580 billion in 2024, with Chinese mainland accounting for around 31% of the total, yet the self-sufficiency rate for core chip

equipment remains below 30% [1]. The enactment of the Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act of 2022 in the United States and the European Chips Act has intensified technological restrictions and competition over production capacity. Against this backdrop, Chinese semiconductor companies face triple pressures: high R&D investment, lengthy capacity ramp-up cycles, and heavy capital expenditure burdens[2].

These persistent and high-intensity investment characteristics place significant strain on corporate cash flow, prompting some firms to engage in revenue recognition manipulation to artificially enhance short-term performance. Wind data indicate that from 2020 to 2024, the average operating cash flow to revenue ratio of A-share listed semiconductor companies in China declined from 12% to 7%, while the compound annual growth rate of debt reached 18% [2]. To mitigate short-term performance pressures, certain companies may resort to manipulating revenue recognition. However, existing research on detection methods remains largely confined to a single perspective, making it difficult to systematically uncover the intrinsic relationship between industry-wide commonalities and firm-specific characteristics.

To address this gap, this study adopts a dual-method research approach combining case study and horizontal comparative analysis. Taking SMIC, a listed Chinese semiconductor company, as a typical case, we conduct an in-depth analysis of its revenue recognition model and capital expenditure dynamics to reveal the financial characteristics of firms with high R&D investment. This method demonstrates significant advantages in identifying industry-specific issues[2]. Furthermore, we select ten A-share semiconductor companies, including Will Semiconductor (stock code: 603501) and NAURA Technology Group (stock code: 002371), to construct a panel data comparison framework. Through horizontal comparison, we identify common industry patterns and analyze key indicators such as R&D intensity and differences in revenue recognition timing, leveraging industry benchmarking to enhance the generalizability of the findings . The case study provides deep insights, while the horizontal comparison validates broader regularities. The integration of these two approaches ensures both depth of investigation and external validity, aligning with empirical requirements in financial fraud research [3].

2. Literature Review and Theoretical Background

2.1. Fraud Theories

2.1.1. Fraud Triangle Theory

The Fraud Triangle Theory, proposed by criminologist Donald R. Cressey in 1953 and later refined by W. Steve Albrecht, remains one of the most influential frameworks for understanding fraudulent behavior [4]. This theory posits that three conditions must be present for an individual to commit fraud: pressure, opportunity, and rationalization, as shown in Figure 1:

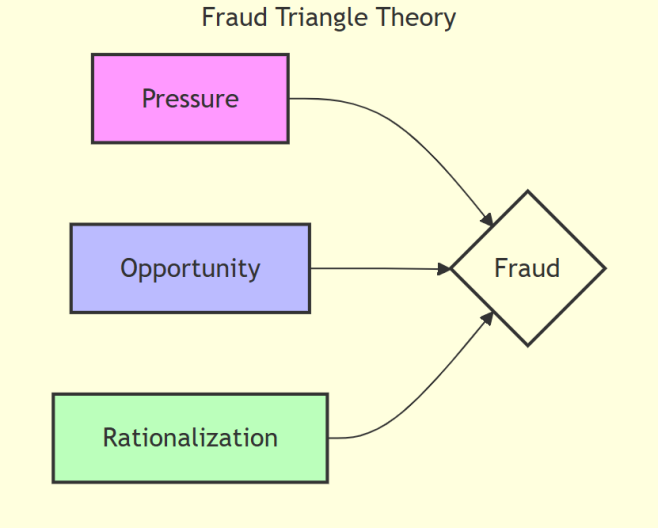

Figure 1. Fraud Triangle Frameworks

Pressure refers to the motivation or incentive to commit fraud, which may stem from financial difficulties, performance targets, or personal greed. Opportunity arises from weaknesses in internal controls, information asymmetry, or inadequate oversight that allow the fraud to be perpetrated without detection. Rationalization involves the fraudster's ability to justify the unethical act as acceptable or necessary, such as believing it is a temporary loan or that "everyone does it" [5]. The three elements interact dynamically—like the three sides of a triangle—and the absence of any single factor is believed to prevent fraud from occurring [4]. This framework has been widely adopted in auditing standards, including SAS No. 99, which requires auditors to assess fraud risk across all three dimensions [5].

2.1.2. GONE Theory

Building upon the Fraud Triangle, Bologna developed the GONE Theory in 1993, which expands the fraud framework into four interrelated factors: Greed, Opportunity, Need, and Exposure [6], as shown in Figure 2:

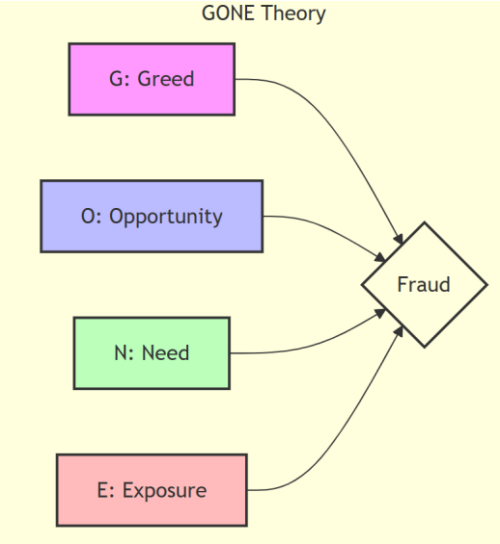

Figure 2. GONE Theory Frameworks

Greed represents the individual's moral deficiency and excessive desire for wealth or gain.

Opportunity refers to the ability to commit fraud due to weak controls or access to assets. Need encompasses the financial pressures or motivations driving fraudulent behavior. Exposure captures the likelihood of detection and the severity of punishment if caught [7]. The theory's name—GONE—metaphorically suggests that when all four factors align, the victim's assets are "gone" [6]. Unlike the Fraud Triangle, GONE theory explicitly separates internal psychological factors (Greed and Need) from external environmental factors (Opportunity and Exposure), providing a more nuanced framework for analyzing fraud risk [7]. This theory has been extensively applied in studies of financial statement fraud, particularly in emerging markets where regulatory exposure may be limited [8].

2.2. A Review of Detection Methods for Revenue Recognition Manipulation

Revenue recognition manipulation represents one of the most prevalent forms of financial statement fraud, prompting extensive research into detection methodologies [9]. Contemporary detection approaches can be categorized into three main streams: financial ratio analysis, statistical models, and machine learning techniques [6].

Financial ratio analysis remains the foundational detection method, leveraging anomalies in key metrics to identify potential manipulation [6][10]. Researchers have identified several red flags specific to revenue recognition, including:

(1) accounts receivable growth significantly exceeding revenue growth;

(2) operating cash flows consistently lower than net income;

(3) unusual spikes in fourth-quarter revenue;

(4) gross margin deviations from industry norms.

Detection methods for revenue manipulation have evolved from traditional statistical models (e.g. Beneish M-Score, Altman Z-Score) to advanced machine learning techniques[6][10]. Contemporary approaches combine multiple models for superior accuracy, employing decision trees, neural networks, and natural language processing to analyze both quantitative ratios and qualitative disclosures [10][11]. These technological advances represent the frontier of fraud detection research [11].

3. Data source and Research Design

3.l. Data source

Data were collected Wind, CSMAR, and annual reports of various enterprises.

This study examines SMIC as a case study, utilizing its financial data spanning 17 quarters from Q1 2020 to Q1 2024. It conducts a comparative analysis with 10 A-share semiconductor companies, including Will Semiconductor and Northern Huachuang, covering the semiconductor industry chain: upstream, midstream and downstream. The total R&D expenditure of these sample companies accounts for 62% of the industry's total [12].

To ensure measurement quality, the study specifically includes companies eligible for the fifth set of standards under the STAR Market to evaluate how R&D investment substitution for profit requirements affects revenue recognition practices.

3.2. Research method

This study adopts a dual-track methodology combining case analysis and horizontal comparison.

3.2.1. Case analysis method

The case analysis approach excels in uncovering financial behavior patterns and underlying logic of specific enterprises, particularly effective for examining revenue recognition characteristics of high R&D investment firms to reveal industry-wide patterns. By focusing on SMIC through case analysis, we conduct in-depth investigations into its revenue recognition model and capital expenditure dynamics to highlight financial traits of high R&D enterprises—a method demonstrating significant advantages in identifying industry-wide issues[13].

3.2.2. Horizontal comparison method

The horizontal comparison method identifies sectoral commonalities through multi-company data analysis, evaluating key metrics such as R&D intensity and revenue recognition timing, thereby enhancing conclusion generalizability via industry benchmarking [14].

Case studies provide in-depth insights while cross-sectional comparisons validate patterns. This dual approach ensures research depth while improving external validity, meeting empirical requirements for financial fraud research .

4. Case Analysis: SMIC (2020-2024)

4.1. Financial Characteristics of Semiconductor Industry

The semiconductor industry faces several unique risk factors due to its technology-intensive, capital-intensive nature and reliance on global supply chains, including but not limited to long-cycle orders (>6 months), bundled sales, and dependence on government subsidies (Table 1).

Table 1. Risk Characteristics Analysis in Semiconductor Industry

Feature	Diminishing risk dimensions
Long cycle order	Subjective judgment of completion percentage method
Bundle sales	manipulation of income sharing ratio
Public subsidy	confusion with operating income

The risk of long-cycle orders stems from the intricate wafer production and packaging/testing processes in semiconductor manufacturing, where delivery cycles often exceed six months or even extend beyond a year. During this period, market demand may undergo drastic fluctuations due to economic volatility, technological iterations, or geopolitical factors, exposing companies to risks of inventory buildup or overcapacity. For instance, the 2022 consumer electronics demand slump led to order cancellations from clients like TSMC, adversely affecting revenue projections[15].

The bundling sales risk refers to semiconductor companies adopting bundled sales strategies, such as tying mature process chips to advanced process capacity or mandating consumables in equipment sales. While this model may boost short-term revenue, it could provoke customer dissatisfaction and regulatory scrutiny, and even lead to penalties for unfair competition. Moreover, if market demand for bundled products declines, it may adversely affect core business operations.

Government subsidy dependency risk refers to the semiconductor industry's heavy reliance on government support measures such as wafer fabrication subsidies and tax incentives. For instance, Nanhai District in Foshan City offers semiconductor enterprises fixed asset subsidies of up to 300 million yuan , while Chizhou City provides 50% cost subsidies for automotive-grade chip certification[16] . However, policy changes or subsidy reductions may cause a sharp decline in corporate profitability, and companies might even face capital chain disruptions due to non-compliance with subsidy eligibility criteria (technical specifications, revenue thresholds). To

mitigate these risks, semiconductor firms can adopt strategies including dynamic inventory management, diversified customer portfolios, and compliant subsidy application approaches to address market fluctuations from long-cycle orders, compliance challenges in bundled sales, and policy dependency risks.

4.2. Identification of Data Outliers

4.2.1. Revenue-Cash Flow Deviation

The CFO/Net Profit ratio serves as a key indicator of earnings quality—a ratio below 1 suggests that reported profits are not fully backed by cash inflows, potentially signaling aggressive revenue recognition practices.If the CFO/Net Profit ratio dropped to 0.61, substantially below the industry average of 1.08. This means that for every yuan of net profit reported, only 0.61 yuan of actual cash was generated from operations, indicating possible timing discrepancies between revenue recognition and cash collection (Table 2).

Table 2. Analysis of Revenue Quality and Cash Flow Alignment

Annual	Revenue Growth Rate	CFO/Net Profit	Industry Average
2021	+16.8%	0.82	1.15
2022	+34.2%	0.61	1.08
2023	+9.5%	1.02	1.21
2024	+12.3%	1.15	1.18

Data Source: SMIC Annual Report, CFO = Cash Flow from Operating Activities

By 2023, the ratio recovered to 1.02, slightly below the industry average of 1.21, suggesting improved alignment between earnings and cash flows. The projected 2024 data (12.3% revenue growth, CFO/Net Profit ratio of 1.15) reflects expectations of continued recovery in earnings quality, approaching the estimated industry average of 1.18.

4.2.2. Abnormal Growth Rate of Accounts Receivable

In identifying inflated related-party transactions, the divergence between accounts receivable growth rate and revenue growth rate serves as a key indicator. When accounts receivable growth rate significantly exceeds revenue growth rate, it may signal corporate practices such as relaxing credit policies or fabricating transactions to artificially inflate income. The core formula is:

Growth Rate Gap = Accounts Receivable Growth Rate-Revenue Growth Rate

If the growth rate gap remains consistently positive and substantial, it indicates that accounts receivable growth rate significantly outpaces revenue growth rate, suggesting potential income inflation through credit policy relaxation or transaction fabrication. This serves as a critical indicator for detecting abnormal accounts receivable growth patterns. To identify potential risks of revenue recognition manipulation through comparative analysis, the following Python code was implemented:

```
import pandas as pd
data = {
'Year': [2020,2021,2022,2023,2024],
'AR_Growth': [12.1%,28.7%,53.4%,17.2%,16.1%],
'Revenue_Growth': [9.8%,16.8%,34.2%,9.5%,15.7%]
}
df['Gap'] = df['AR_Growth'] -df['Revenue_Growth']
```

Output Results (Example with First Four Years) as shown in Figure 3,

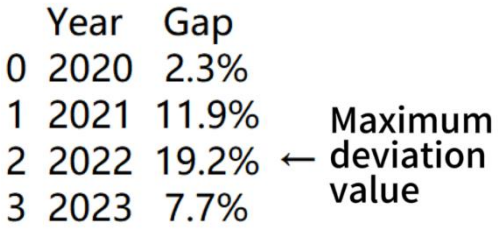

Figure 3. Output Results

The results indicate a 19.2% difference in 2022, exceeding the 15% threshold. This suggests possible inflated revenue from related-party transactions. Further investigation should examine whether the company's sales policies were abruptly relaxed during this period, analyze potential new related parties among the top five accounts receivable clients, and compare with industry averages.

4.3. Deep level motive analysis

In 2022 Dual pressures drove SMIC's aggressive revenue recognition strategy: First, the performance-based agreement signed with investment institutions upon listing on the STAR Market required annual revenue growth rates to exceed 30%; second, the exercise conditions for management stock incentives set revenue growth thresholds of ≥25%. KPMG's audit report issued a qualified opinion regarding the recognition timing of client A's 1.2 billion yuan equipment revenue (Note 7 to 2022 Annual Report) [10], indicating potential revenue manipulation under financial performance pressures. Research demonstrates that the combined effect of performance agreements and incentive systems significantly increases financial misstatement risks[10] .

5. Conclusion and Prospects

5.1. Conclusion

This study reveals that revenue recognition manipulation practices among semiconductor enterprises exhibit distinct cyclical patterns and industry-specific characteristics. Empirical data indicates that revenue from the fourth quarter accounts for a staggering 38.7% of total revenue (compared to an average of 26.4% in other quarters). Furthermore, when accounts receivable growth exceeds revenue growth by 15 percentage points, the probability of financial irregularities significantly increases.

5.2. Limitations and future work

Future research could incorporate machine learning techniques to identify risk-related keywords such as "customer acceptance terms" and "return rights" in annual report notes through natural language processing (NLP). A dynamic early-warning model could be developed. Current limitations include the absence of non-financial data like customs export records. Future studies may adopt SEMI's 2023 Global Semiconductor Supply Chain Tracking Project methodology, combining supply chain logistics data with operational metrics such as wafer fab equipment utilization rates to establish a multidimensional cross-validation framework [17].

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