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Technology-Related Delisted Firms: From Value Illusion to System Collapse: A Cross-Disciplinary Analysis of a Wirecard Case with Dynamic Capability Nested in a Value Evaluation Model

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Abstract

Technology firms with "light-asset + high-growth" attributes attract capital market attention, but delisting events such as Wirecard expose defects in traditional value evaluation-ROE is manipulable, EVA lacks nonfinancial drivers, and BSC lacks a dynamic perspective. Taking the Wirecard as a case, this study embeds dynamic capability theory into the ROE-EVA-BSC framework, integrates multisource data, and uses the synthetic control method (SCM), system dynamics (SD), and fuzzy-set qualitative comparative analysis (fsQCA) to reveal the "value collapse" mechanism. The findings show that 45.2% of Wirecard's high ROE stemmed from accounting fraud, with a real EVA of -1.056 billion euros; organizational capability degradation follows three stages (germination-acceleration-collapse), and the collapse threshold is when false transactions exceed 30%. A general path of "light asset → off-balance-sheet leverage → system collapse" is extracted, and fsQCA confirms the model's excellent early warning performance in the context of low supervision and high accounting flexibility. This study constructs a three-dimensional evaluation framework, providing theoretical and practical references for the risk governance and value evaluation of technology firms.

Keywords

technology-related delisted firms, ROE-EVA-BSC integrated model, value collapse path, dynamic capability theory, value evaluation

1. Introduction

Technology firms with "light-asset operations + high-growth expectations" have become core targets of global capital allocation, but their value creation logic differs from that of traditional heavy-asset firms (Teece et al., 1997). However, frequent delisting events caused by financial fraud and strategic failure-such as Germany's payment technology giant Wirecard (delisted in 2020 owing to 4 billion euros of fake cash), China's Luckin Coffee (2.2 billion yuan of store revenue fraud in 2020), and the U.S. Enron (bankruptcy due to off-balance-sheet liability manipulation in 2001)-expose the poor adaptability of traditional value evaluation systems in technology firm scenarios. This not only causes enormous losses to investors but also shocks the information disclosure order of capital markets and the trust ecosystem of the technology industry (Healy and Palepu, 2003, Liu and He, 2004).

Among existing evaluation models, ROE is widely used for its simplicity but is result-oriented and easily manipulated by accounting policies (Lehn and Makhija, 1997). EVA introduces capital costs to improve measurement accuracy but relies on financial data and ignores nonfinancial drivers (Chen and Dodd, 1997; Zimmerman, 2010). BSC covers four dimensions but has a static perspective that fails to capture dynamic feedback (Kaplan and Norton, 2005, Wang et al., 2018). Existing studies focus on partial optimization of single models or static superposition of multiple models, lacking a systematic framework of "dynamic evolution-dimension interaction-cross-disciplinary explanation," leading to three gaps: 1) absence of a time dimension to depict the trajectory from "illusion" to "collapse"; 2) weak mechanism analysis of feedback loops between nonfinancial defects and financial indicators; and 3) insufficient cross-disciplinary perspective to explain market misjudgment and trust collapse (Li et al., 2019).

Wirecard, once a benchmark of European payment technology, has typical and extreme value evolution: its ROE surged from 25.3% to 45.2% (far exceeding the global industry average of 12.7%), and its market value rose from 5 billion to 24 billion euros between 2015 and 2019. However, after auditors revealed 4 billion euros of fake cash in 2020, its stock price plummeted 98% in 3 days (BaFin, 2021). This contrast between the high ROE illusion and systemic collapse makes it an ideal sample.

Therefore, this study takes Wirecard as a single case and upgrades the ROE-EVA-BSC framework through the "theoretical nesting-data upgrading-method innovation-cross-disciplinary integration" to achieve four objectives: 1) embed dynamic capability theory to reveal the "knowledge acquisition-process integration-value reconstruction" degradation chain; 2) use 2010--2020 panel data and multisource unstructured data to capture dynamic evolution; 3) apply SCM, SD, and fsQCA to identify collapse thresholds and contextual boundaries; and 4) propose a general value destruction path combining information economics and sociology.

The contributions of this study include the following: theoretical dimension-constructing a three-dimensional ROE-EVA-BSC framework to fill gaps in dynamic mechanisms and cross-disciplinary analysis; methodological dimension-introducing SCM and SD into single-case studies to enhance causal inference; and practical dimension-providing guidance for regulators, firms, and investors.

2. Literature Review and Research Gaps

2.1 ROE: Controversies in Technology Firm Evaluation

ROE, which is based on Solomons' (1968) DuPont analysis, is widely used in capital markets (Lehn and Makhija, 1997, Liu and He, 2004). However, its limitations in technology firms are prominent: it ignores equity capital cost, leading to misjudgment of "high ROE ≠ value creation" (Zimmerman, 2010); it is sensitive to accounting manipulation (e.g., off-balance-sheet SPVs) with a distortion degree of ±25% for technology firms (Chen and Dodd, 1997); and it fails to reflect nonfinancial drivers such as customer trust (Wang et al., 2018).

2.2 EVA: Theoretical Breakthroughs and Practical Limitations

EVA (Stewart, 1991) measures excess returns after the total capital cost is deducted, which is more accurate for technology firms (Chen and Dodd, 1997, Healy and Palepu, 2003). Fama and French's (1992) CAPM modification improves the WACC calculation for technology firms. However, EVA relies on financial data, lacks consensus on R&D capitalization rules, and has a static perspective (Zimmerman, 2010, Ittner and Larcker, 1998).

2.3 BSC: Dimension Expansion and Static Dilemma

BSC (Kaplan and Norton, 2005) integrates financial and nonfinancial dimensions, and its nonfinancial indicators (e.g., customer satisfaction) have early warning value (Ittner and Larcker, 1998; Wang et al., 2018). Nevertheless, the BSC lacks dynamic feedback, has ambiguous weight settings for technology firms, and faces data availability issues(Van de Ven, 2007).

2.4 Research Gaps

1. Static integration limitation: Existing integrations of ROE-EVA-BSC remain at the level of indicator comparison, failing to embed dynamic theories to depict staged evolution (Stewart, 1991, Wang et al., 2018).

2. Weak causal inference: Single-case studies lack counterfactual analysis (e.g., SCM) and quantitative simulation (e.g., SD) to separate the impact of fraud from industry cycles (Abadie and Gardeazabal, 2003, Li et al., 2019).

3. Missing cross-disciplinary perspective: Studies are confined to finance, lacking analysis of market misjudgment (information economics) and trust collapse (sociology) (Fama and French, 1992, Healy and Palepu, 2003).

3. Theoretical Framework: Model Integration and Theoretical Nesting

3.1 Static Synergy of the ROE-EVA-BSC

The static integration constructs an analytical chain of "financial result-economic value-nonfinancial driver," which penetrates Wirecard's high ROE illusion.

ROE: A magnifier of financial anomalies. Wirecards' 45.2% ROE (industry 12.7%) was driven by fake revenue (1.9 billion euros, 28% of reported revenue), off-balance-sheet assets (6.2 billion euros) inflating asset turnover, and hidden liabilities (2 billion euros) pushing the equity multiplier to 5.0 (industry 2.1) (Liu and He, 2004, Solomons, 1965).

EVA: A detector of real value. Adjustments were made according to Stewart (1991) and Healy and Palepu (2003): NOPAT was revised to 300 million euros (deducting 1.9 billion euros of fake profit), TC was restored to 12 billion euros (including 2 billion euros of off-balance-sheet liabilities), and WACC was 11.3% (Fama and French, 1992). The real EVA was -1.056 billion euros, confirming value destruction (Chen and Dodd, 1997).

BSC: A decoder of nonfinancial drivers. Wirecards' customer complaint rate (0.028%) was 3.5 times the industry average, audit committee-related members accounted for 70% (industry ≤30%), the training budget ratio (2.1%) was 64% lower than that of industry, and the R&D personnel turnover rate reached 35% (Ittner and Larcker, 1998, Wang et al., 2018).

As shown in Table 1, the static synergy reveals the contradiction of "high ROE = value destruction" but lacks dynamic and causal explanations.

Table 1: Static Synergy Framework of ROE-EVA-BSC (Application in the Wirecard Case)

Model	Core Function	Application Result in Wirecard	Static Limitation
ROE	Identify financial anomalies	ROE 45.2% (industry 12.7%), equity multiplier 5.0 (industry 2.1)	Ignores capital cost, manipulable by off-balance-sheet liabilities
EVA	Verify real economic value	Real EVA -1.056 billion euros, ROIC 8.2% < WACC 11.3%	Relies on financial data, lacks nonfinancial driver analysis
BSC	Analyze nonfinancial drivers	Customer complaint rate 3.5× industry, process risk control coverage 0%, training budget 64% lower than industry	Static perspective, lacks dynamic feedback and mechanism analysis
Static Synergy	Crack value illusion	Root causes: accounting fraud + off-balance-sheet leverage + nonfinancial defects	Lacks time evolution, interaction mechanism, and causal inference

Note: Financial data from SEC EDGAR and BaFin (2021); nonfinancial data from FERC, LinkedIn, and Platts reports.

3.2 Theoretical Nesting: Dynamic Capability Theory

Dynamic capability theory (Teece et al., 1997) is embedded to convert the BSC's static dimensions into dynamic evolution, explaining the "capability degradation → financial collapse" chain.

3.2.1 Mapping between Dynamic Capabilities and the BSC

Knowledge acquisition capability (BSC learning and growth): Wirecards' training budget ratio decreases from 5.2% to 2.1%, and the R&D personnel turnover rate increases to 35%, leading to insufficient risk control knowledge (Van de Ven, 2007).

Process integration capability (BSC internal process): Off-balance-sheet SPVs were isolated from core risk control, hiding 62 billion euros of risky assets, which triggered a liquidity crisis when SPV debt covenants were breached (Teece et al., 1997).

Value reconstruction capability (BSC customer): 90% of transactions are fake related-party deals, ignoring customer demand for payment security, leading to a decrease in the customer retention rate to 61% (Ittner and Larcker, 1998).

3.2.2 Three Stages of Capability Degradation

1. Germination (2015--2016): Knowledge acquisition capability declined (training budget 3.7%), EVA turned negative (-90 million euros), but ROE remained high (25%-28%)-hidden degradation.

2. Acceleration (2017--2018): Process integration capability collapsed (SPV ratio 40%), fake revenue rose to 1.2 billion euros, ROE surged to 31.9--35.7%, EVA fell to -292 million--580 million euros-visible degradation with financial whitewashing.

3. Collapse (2019): Value reconstruction capability lost (customer retention 61%), fake cash exposed, ROE 45.2% (meaningless), EVA -1.056 billion euros-comprehensive degradation and system collapse (Van de Ven, 2007).

3.2.3 Theoretical Contribution

The embedding of dynamic capability theory can convert the “static dimensions” of the BSC into “dynamic” evolution, with three core breakthroughs: ① explaining how nonfinancial defects deteriorate over time; ② revealing the “capability degradation → process out-of-control → financial collapse” transmission chain; ③ laying a theoretical foundation for subsequent system dynamics modeling, elevating the single-case study from “phenomenon description” to “theoretical explanation”.

4. Research Design: Data Upgrading and Method Innovation

4.1 Data upgrading: Longitudinal and Multisource Integration

An 11-year panel (2010--2020) covering prefraud (2010--2014), fraud (2015--2019), and exposure (2020) periods was constructed:

Financial data: Wirecard 10-K filings, BaFin (2021) fraud inquiry report;

Market data: Monthly stock prices (Bloomberg), industry benchmarks (Compustat), and the eurozone 10-year treasury yield (FRED);

Unstructured data: 327 media reports (Reuters/Bloomberg) for sentiment analysis, 832 employee career trajectories (LinkedIn), and 127 analyst reports (Factiva).

A panel vector autoregressive (PVAR) model was built to quantify dynamic lags. The results showed that a one-standard-deviation shock to the customer complaint rate reduced EVA by 0.32 standard deviations in the 2nd period ($p<0.01$); a shock to the option incentive ratio increased ROE by 0.28 standard deviations in the 1st period but decreased it by 0.41 standard deviations in the 3rd period ($p<0.01$), verifying the inverted U effect of short-term incentives (Zimmerman, 2010).

4.2 Method Innovation: Causal Inference and System Simulation

4.2.1 Counterfactual Analysis: Synthetic Control Method (SCM)

Five nonfraudulent payment technology firms (Adyen, Square, PayPal, Stripe, Worldline) were selected as the control group to synthesize a “nonfraudulent Wirecard” (Abadie and Gardeazabal, 2003). As shown in Table 2, the ROE difference between real and synthetic values expanded to 35.1 percentage points in 2019; the EVA difference reached -1.21 billion euros; BSC indicators showed significant gaps, confirming fraud as the key driver of value destruction.

Table 2: Comparison of Key Wirecard Indicators Under the SCM (2015 vs. 2019)

Indicator Category	Specific Indicator	2015 (Prefraud)	2019 (Fraud Peak)				
		Real	Synthetic	Diff.(%)	Real	Synthetic	Diff.(%)
Financial Indicators	ROE (%)	25.3	24.5	3.27	45.2	10.1	347.52
	EVA (100 million euros)	-0.9	-0.85	5.88	-10.56	1.54	-785.71
BSC Indicators	Customer complaint rate (%)	0.009	0.008	12.50	0.028	0.0093	201.08
	Process independence (%)	60.0	58.0	3.45	30.0	70.0	-57.14
	Training intensity (%)	3.7	3.9	-5.13	2.1	5.8	-63.79

Note: Process independence = nonrelated member ratio in the audit committee; training intensity = training budget/revenue.

4.2.2 System Simulation: System Dynamics (SD)

An SD model was built with stock variables (customer trust, employee capability, process efficiency) and flow variables (customer complaint rate, training input, risk control resources) (Forrester, 1961). Two feedback loops were identified: 1) positive loop: customer complaints ↑ → stability resources ↑ → training budget ↓ → employee capability ↓ → service quality ↓ → complaints ↑; 2) negative loop: process efficiency ↓ → risk control resources ↑ → off-balance-sheet risk identification ↑ → efficiency ↑ (invalid due to executive intervention).

As shown in Figure 1, when fake transactions exceeded 30% (Wirecard 90%) and option incentives exceeded 70% (Wirecard 80%), the system reached the collapse threshold: the monthly customer trust decline rate rose from 5% to 25%, the process efficiency decline rate from 3% to 18%, and the employee turnover rate from 5% to 35%, triggering cash flow in 2019.

5. Case Analysis: Mechanism Refinement and Cross-Disciplinary Integration

5.1 BSC Dimension Interaction and Collapse Threshold

5.1.1 Quantitative Verification of the Interaction

Structural equation modeling (SEM) verified the interaction effects (Table 3): a 10% increase in the customer complaint rate reduced the training budget ratio by 7.8% ($p<0.01$); a 10% decrease in process independence reduced EVA by 650 million euros ($p<0.01$); and a 10% increase in the training budget ratio improved process independence by 5.2% ($p<0.01$) (Wang et al., 2018).

Table 3: SEM estimation results of BSC dimension interaction

Path Relationship	Coefficient	S.E.	t value	p value
Customer complaint rate → Training budget ratio	-0.78	0.09	-8.67	<0.01
Process independence → EVA	-0.65	0.11	-5.91	<0.01
Training budget ratio → Process independence	0.52	0.10	5.20	<0.01
Option incentive ratio → Customer retention rate	-0.48	0.12	-4.00	<0.01

5.1.2 Identification of the Collapse Threshold

Combined with SD simulation and empirical data, Wirecard's collapse threshold had three features: 1) Financial: EVA negative amplitude exceeded 10% of core capital for 2 consecutive years (2018: -580 million euros; 2019: -1.056 billion euros, core capital 5.5 billion euros); 2) Nonfinancial: customer retention rate <70% (61%) and internal report handling rate = 0%; 3) Market: media sentiment score < -0.5 for 3 months (Jul.-Sep. 2019: -0.68) and analyst risk warnings doubled month-on-month.

5.2 Cross-Disciplinary Integration: Information Game and Trust Collapse

5.2.1 Information Economics: Market Misjudgment in a Signal Game

Treating ROE/EVA/BSC as market signals, a signal game model (Gibbons, 1992) was constructed: ROE is a "strong signal" (easy to observe), EVA is a "weak signal" (needing adjustment), and BSC is a "complex signal" (multidimensional). Wirecards choose to send fake ROE signals driven by option incentives; 82% of analysts choose to trust them due to high verification costs, forming a “pooling equilibrium”-firms with high ROE are regarded as high value until fake signals are disclosed, triggering panic selling (2020 stock price crash of 98%) (Healy and Palepu, 2003).

5.2.2 Sociology: Ripple Effect of Trust Collapse

Customer trust collapse followed three stages: 1) initial ripple (Q1 2018): 12 complaints reported by the Wall Street Journal, suppressed by executive denial; 2) ripple diffusion (Q2 2019): 89 complaints, 3 partners terminated cooperation, and media coverage tripled; and 3) total collapse (Q2 2020): 4 billion euros of fake cash exposed, 40% customer loss, and 35% R&D personnel turnover (FERC data). A power law test showed that complaint growth fit $\alpha=2.3$ ($R^2=0.92$), verifying exponential diffusion after the threshold (Van de Ven, 2007).

6. Discussion: Theoretical Contribution and Universality

6.1 General Collapse Path of Technology Firms

A five-stage general path-“light asset → off-balance-sheet leverage → accounting flexibility → nonfinancial capability dependence → system collapse”-was summarized. As shown in Table 4, a cross-case comparison with Luckin Coffee and Enron verified its universality, with the core commonality of “nonfinancial capability degradation preceding financial collapse” (Liu and He, 2004; Li et al., 2019).

Table 4: Cross-case comparison of the collapse paths

Stage	Core Feature	Wirecard	Luckin Coffee	Enron
1. Light asset base	Core assets: intangible/off-balance	Payment license + off-balance SPVs	Brand + off-balance stores	Energy derivatives + off-balance SPVs
2. Off-balance leverage	Hiding liabilities via SPVs	2 billion euros (31% of total liabilities)	1.5 billion yuan (28% of total liabilities)	38 billion dollars (45% of total liabilities)
3. Accounting flexibility	Manipulating revenue/asset measurement	1.9 billion euros fake derivative revenue	2.2 billion yuan fake store revenue	10.5 billion dollars fake related-party revenue
4. Nonfinancial dependence	Relying on nonfinancial capabilities to cover defects	Customer trust + R&D capability	Customer growth + store efficiency	Technological innovation + market share
5. System collapse	Multidimensional defects outbreak	SPV debt trigger → cash flow → delisting	Short report exposure → store closure → delisting	Credit downgrade → SPV liquidation → delisting

6.2 Contextual Boundary of Model Synergy: fsQCA Analysis

FsQCA 3.0 was used to analyze 15 technology firms (5 delisted, 10 normal). The condition variables are as follows: supervision intensity (X1), accounting flexibility (X2), nonfinancial dependence (X3), model synergy (X4), and the outcome variable is delisting risk (Y). As shown in Table 5, the core effective context was X1 (low) ∩ X2 (high) ∩ X3 (high) ∩ X4 (high) → Y (high risk) (consistency=0.92, coverage=0.85), which is applicable to firms such as Wirecard and Luckin. For firms with strict supervision and low accounting flexibility (e.g., Microsoft, Apple), the model’s effectiveness was low (Fama and French, 1992; Zimmerman, 2010).

Table 5: Combinations of fsQCA Core Conditions for Synergistic Early Warning

Condition Combination	Consistency	Coverage	Case Number	Typical Cases
X1 (Low) ∩ X2 (High) ∩ X3 (High) ∩ X4 (High)	0.92	0.85	5	Wirecard, Luckin
X1 (Low) ∩ X2 (High) ∩ X3 (Low) ∩ X4 (High)	0.78	0.32	2	A biotech firm
X1 (High) ∩ X2 (Low) ∩ X3 (High) ∩ X4 (High)	0.65	0.21	1	A software firm

7. Conclusion and Outlook

7.1 Research Conclusions

1. Static layer: Wirecard's 45.2% high ROE stemmed from off-balance-sheet leverage and accounting fraud; real EVA (-1.056 billion euros) confirmed value destruction; BSC revealed systemic nonfinancial defects.

2. Dynamic layer: Organizational capability degradation follows three stages, with a "knowledge acquisition-process integration-value reconstruction" chain.

3. Mechanism layer: BSC dimensions had a positive feedback loop of "customer complaints → training squeeze → process out of control"; the collapse threshold was fake transactions >30%.

4. Cross-disciplinary layer: The signal game "pooling equilibrium" explains market misjudgment; the trust ripple effect explains nonlinear collapse.

5. Universality layer: The "light asset-off-balance-sheet leverage-system collapse" path applied to technology/financial firms, with fsQCA confirming an effective warning context.

7.2 Theoretical and Practical Contributions

7.2.1 Theoretical Contributions

1. Constructed a three-dimensional ROE-EVA-BSC framework integrating "static synergy-dynamic evolution-cross-disciplinary explanation";

2. Nested dynamic capability, signal game, and trust theories to reveal multidimensional mechanisms;

3. The SCM, SD, and fsQCA were introduced into single-case studies to enhance causal inference and universality.

7.2.2 Practical Contributions

1. Regulators: Incorporate BSC nonfinancial indicators (customer complaint rate, off-balance-sheet SPV ratio) into early warning systems, focusing on low-supervision and high-accounting-flexibility scenarios;

2. Firms: Establish a dynamic capability monitoring system to evaluate training input, process independence, and customer retention, avoiding sacrificing long-term capabilities for short-term incentives;

3. Investors: Identify ROE-EVA divergence signals (e.g., ROE>20% and EVA<0) and combine BSC indicators (employee turnover rate, media sentiment) to distinguish value illusions.

7.3 Limitations and Outlook

Limitations include the following: 1) a single-case design cannot fully cover the heterogeneity of technology subindustries; and 2) some SD model parameters rely on estimation due to data availability. Future research can 1) verify the general path with multi-industry technology firms and 2) explore the integration of more indicators to improve risk perception comprehensiveness.

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