

Artha: Journal of Business and Finance

Vol. 01 Issue 02

December 2025

Contents

Editorial

Vivek Rajvanshi

Articles

FinTech and Financial Inclusion: Unpacking the Links to Inequality
Catarina Figueira & Lakshmy Subramanian

Drivers of Debt-Financing and Related Sustainability Costs: A Pre- and Post GST Perspective of Indian Consumer Goods SMES
Sayak Mitra

Emerging Technology in Financial Crime Compliance
Sriram Narasimhan

Does Entrepreneurship Drive Economic Growth? Insights from India
Sagartirtha Chakraborty & Suresh Kumar Nath

Green Sill Capital Fiasco: A Recipe for Disaster & Deceit
Anil Kumar Pandey



Published by:

Financial Research and Trading Laboratory (FRTL),
Indian Institute of Management Calcutta, Kolkata (India)



Editorial Board



Dr. Vivek Rajvanshi
Professor, Finance & Control Group
Coordinator, Financial Research & Trading Laboratory
Indian Institute of Management Calcutta
Email: vivekr@iimcal.ac.in



Dr. Anirban Banerjee
Assistant Professor,
Finance & Accounting
Indian Institute of Management Ahmedabad
Email: anirbanb@iima.ac.in



Dr. Madhusudan Karmakar
Professor,
Finance & Accounting
Indian Institute of Management Lucknow
Email: madhu@iiml.ac.in



Dr. Praveen Bhagawan M
Associate Professor,
Accounting and Finance
IFMR GSB, Krea University
Email: praveen.bhagawan@krea.edu.in



Dr. Samit Paul
Associate Professor,
Finance & Control Group
Indian Institute of Management Calcutta
Email: samit@iimcal.ac.in



Dr. Sudhakara Reddy
Associate Professor,
Finance & Control Group
Indian Institute of Management Calcutta
Email: sudhakar@iimcal.ac.in



Dr. Varun Jindal
Assistant Professor
Finance & Accounting
Indian Institute of Management Bangalore
Email: varun.jindal@iimb.ac.in



Dr. Kaushik Roy
Assistant Professor,
Strategic Management Group
Indian Institute of Management Calcutta
Email: kaushik@iimcal.ac.in



Dr. Neerav Nagar
Associate Professor,
Finance & Accounting
Indian Institute of Management Ahmedabad
Email: neeravn@iima.ac.in



Dr. R Rajesh Babu
Professor,
Public Policy and Management Group
Indian Institute of Management Calcutta
Email: rajeshbabu@iimcal.ac.in



Dr. Sankarshan Basu
Professor,
Finance & Accounting
Indian Institute of Management Bangalore
Email: sankarshan.basu@iimb.ac.in



Dr. Sudarshan Kumar
Assistant Professor,
Finance & Control Group
Indian Institute of Management Calcutta
Email: sudarshank@iimcal.ac.in



Dr. V K Unni
Professor,
Public Policy & Management Group
Indian Institute of Management Calcutta
Email: unniv@iimcal.ac.in

Editorial Office

Ms. Priyanka Dasgupta
Assistant Manager,
Financial Research & Trading Laboratory (FRTL)
Email: artha@iimcal.ac.in

IIM Calcutta, P.O. Joka, D.H. Road,
Kolkata 700104, West Bengal
+91-33-7121-1141

Contents

2

Editorial

Vivek Rajvanshi

4

Contributors

6

FinTech and Financial Inclusion: Unpacking the Links to Inequality

Catarina Figueira & Lakshmy Subramanian

27

Drivers of Debt-Financing and Related Sustainability Costs: A Pre-and Post GST Perspective of Indian Consumer Goods SMES

Sayak Mitra

40

Emerging Technology in Financial Crime Compliance

Sriram Narasimhan

50

Does Entrepreneurship Drive Economic Growth? Insights from India

Sagartirtha Chakraborty & Suresh Kumar Nath

60

Green Sill Capital Fiasco: A Recipe for Disaster & Deceit

Anil Kumar Pandey



Artha: Journal of Business and Finance, Vol 1(2)


<https://www.iimcal.ac.in/artha>

Editorial



Dear Reader,

Welcome to December 2025, Volume 1, Issue 2 of **Artha: Journal of Business and Finance**. This peer-reviewed e-journal is dedicated to showcasing high-quality contemporary research, with a primary focus on Accounting, Finance, and Corporate Governance. We are pleased to present this issue to you, and we hope the articles published herein offer valuable insights and lead to meaningful academic and professional discussions.

The article ***“FinTech and Financial Inclusion: Unpacking the Links to Inequality”*** examines how financial technology (FinTech) shapes financial inclusion and inequality across countries using Global Findex data (2011–2021). The study finds that FinTech expands financial inclusion but has mixed distributional effects. Overall, the paper highlights financial inclusion as the key transmission channel through which FinTech influences inequality, underscoring the need for context-specific, inclusion-focused policies.

The next article, ***“Drivers of Debt-Financing and Related Sustainability Costs: A Pre-and Post GST Perspective of Indian Consumer Goods SMES,”*** investigates how India’s Goods and Services Tax (GST) reshaped debt financing decisions of consumer goods SMEs by altering sustainability-related operating costs. GST reduced tax compliance and logistics costs, improved transparency, and simplified interstate trade, thereby strengthening firms’ capital structure decisions. Post-GST, profitability and liquidity reduced reliance on debt.

The third article, ***“Emerging Technology in Financial Crime Compliance,”*** analyses the impact of the rapid sophistication of financial crime is pushing banks and financial institutions to adopt AI and machine learning, even as regulatory scrutiny demands cautious implementation. The author argues that the traditional rule-based systems are proving inadequate, plagued by delays and false positives. Emerging technologies—ranging from

machine learning and generative AI to agentic and quantum AI—are transforming fraud detection, AML, KYC, and sanctions screening. The future of financial crime compliance lies in explainable, regulator-aligned, human-in-the-loop AI systems that enhance resilience without compromising trust.

The next article, *“Does Entrepreneurship Drive Economic Growth? Insights from India,”* analyses the impact of the entrepreneurship ecosystem on India’s economic growth, innovation, and productivity. Drawing on time-series data from 2001–2024, this study shows a robust, positive relationship between early-stage entrepreneurial activity and GDP per capita, reinforcing the role of entrepreneurs as engines of market dynamism and knowledge diffusion. Government investment further amplifies growth, while unemployment continues to weigh on economic performance.

The last article, *“Green Sill Capital Fiasco: A Recipe for Disaster & Deceit,”* examines the 2021 collapse of Greensill Capital to highlight the risks embedded in alternative finance and supply-chain funding. Greensill’s rapid growth rested on reverse factoring, dense networks, private equity backing, and insured securitization, with heavy exposure to the GFG Alliance. As leverage rose and transparency declined, risk became dangerously concentrated. When insurance was withdrawn, investor confidence collapsed, triggering a liquidity crisis that rippled across banks, suppliers, and governments. The case underlines a central lesson: strategic shortcuts and opaque networks may fuel growth, but they ultimately destabilize entire supply chains.

We hope you enjoy reading the diverse articles in this issue and extend our heartfelt thanks to the authors for their valuable contributions. We warmly encourage you to consider Artha: Journal of Business and Finance as a platform for sharing your original research articles. Please submit your submissions and feedback to artha@iimcal.ac.in. We look forward to your continued support and active participation in the future.

Vivek Rajvanshi

Chief Editor

Contributors



Catarina Figueira is a Professor of Applied Economics and Policy and the Director of Education at Cranfield School of Management. Her research interests include financial modelling, institutional performance, and the effects of regulatory changes. She has also published work examining the relationship between corporate governance and company performance, the value of board diversity, and the importance of cosmopolitanism in fostering entrepreneurship.



Lakshmy Subramanian is a Lecturer in Financial Economics at the Cranfield School of Management and has a background in economics and management. Her research interests include financial inclusion, digital finance including digital currencies, emerging trends in banking, inequality, and trends in consumption.



Sayak Mitra is an Assistant Professor (in Accounting & Finance Group) at the Department of Management Studies, St. Xavier's College (Autonomous), Kolkata. He has over six years of teaching experience at the UG level in both Commerce and Management disciplines. His research interests include Corporate Finance & Financial Management, Behavioral Finance, Financial Market, Financial Econometrics, and Financial Statement Analysis.



Sriram Narasimhan is a Senior Director at LTIMindtree, where he leads the Regulatory Compliance Practice. An alumnus of the PGDM (36th batch, 1999–2001) program at the Indian Institute of Management Calcutta, he is a technology leader with over 25 years of experience in Indian multinational IT services firms. His professional expertise lies in delivering regulatory compliance solutions for international Banking and Financial Services clients.



Sagartirtha Chakraborty is a Ph.D. Research Scholar in the Department of Economics at Cotton University, Assam. His work focuses on the areas of international relations, entrepreneurial ecosystems, and contemporary policy narratives on geopolitics. His work has also appeared across several internationally recognised platforms, including the London School of Economics and Political Science, Leiden Madtrics, Eurasian Review, along with Assam Statistical Atlas, and more than 15 edited volumes.



Suresh Kumar Nath is an Associate Professor in the Department of Economics at Cotton University, India. He served as the Registrar of Gauhati University, Assam during 2014-2019. His work focuses on the areas of entrepreneurship development, educational economics, and policy narratives on gender and migration. Dr. Nath's peer-reviewed articles are published in various journals, including Small Enterprises Development Management & Extension (SEDME), Space & Culture, Socio-Economic Challenges, Gauhati University Institute of North East India Studies (GUINEIS), Srotaswini etc., to name a few.



Anil Kumar Pandey is an Associate Professor at Acharya Bangalore Business School (ABBS), Bengaluru, specializing in Corporate Finance and Financial Management. He holds a PhD from the National Institute of Industrial Engineering (NITIE), Mumbai. His research interests include corporate finance, financial markets, financial strategy, risk management, market microstructure, monetary policy transmission, corporate governance, and the interface between finance, regulation, and sustainability. He has authored and co-authored several research papers, case studies, and pedagogical materials, and regularly contributes to discussions on financial innovation, corporate failures, and regulatory challenges.

Note: The views expressed by the authors in their articles published in this issue of Artha: Journal of Business and Finance are personal and do not necessarily represent the views of their employers, or that of Artha: Journal of Business and Finance, FRTL, and IIM Calcutta. Authors are responsible for any permission needed for the copyrighted materials used in their article.



FinTech and Financial Inclusion: Unpacking the Links to Inequality

Catarina Figueira^a, Lakshmy Subramanian^b

^{a,b}*Cranfield School of Management, UK*

Abstract

This investigation analyses how financial inclusion, dimensions of inequality and financial technology (FinTech), are related across 113 countries using data from the 2011–2021 Global Findex survey. The study finds both direct and indirect associations between the different constructs employing structural equation modelling methodologies. The primary findings reveal that FinTech simultaneously worsens income inequality while narrowing gender gaps through enhanced financial inclusion. Additionally, these technologies promote broader financial participation among excluded sections of the population. Greater financial inclusion lowers both economic and gender-based inequalities. The research also explains that effective regulation, educational opportunities, and availability of credit can contribute to more equitable outcomes through financial inclusion. These findings add to emerging scholarships on how financial technological innovation and robust financial inclusion initiatives can improve resource allocation and promote more inclusive economic development globally. This represents the first comprehensive examination of multiple inequality types and their complex relationships within this framework. The study provides preliminary evidence of the varying distributional implications of technology-based finance and financial inclusion on several types of inequalities.

Keywords: FinTech, Financial inclusion, Income Inequality, Gender Inequality Structural Equation Modelling

1. Introduction

There has been considerable attention on the dynamic between different facets of finance and various dimensions of inequality (Altunbaş & Thornton, 2019; Nguyen & Nasir, 2021; Demir et al., 2022). These studies accentuate the essentiality of financial establishments, markets, and other stakeholders in resource allocation, which drives economic growth (Murinde, 2012). Gaining access to finance enables low-income individuals to pursue income-generating opportunities, contributing to investment, employment, and economic development (Basu, 2008). Studies also show a strong connection between expanding financial access and narrowing inequality. Enhancing access to commercial banks for low-income individuals improves their wellness (Danladi et al., 2023; Ali, 2022). The UN 2030 Agenda highlights holistic financial access as a driver in the realization of the Goals for Sustainable Development (Azmeah, 2025; Carè et al., 2025)

There is increasing optimism about financial technology (FinTech) and its prospects to strengthen financial inclusion by promoting inclusive finance at lower costs (Philippon, 2019; Berg et al., 2025; Edigbonya & Tioluwani, 2022; Ferilli et al., 2024; Jena, 2025). Mobile financial services may help integrate underbanked populations into the regulated financial network, promoting growth and development which is equitable and balanced (Demirgüç-Kunt et al., 2020). FinTech can also transform business engagement with suppliers and other stakeholders (Cumming et al., 2021)

Under this backdrop, this paper explores the relationships linking financial technology, financial inclusion, and inequality dimensions across 113 nations using 2011–2021 Global Findex survey database. Our objectives are threefold: first, to assess how FinTech influences inequality; second, study the manner in which financial inclusion is influenced by FinTech and contributes to inequality; and third, to analyze how enabling factors, like regulatory quality, education, and financial deepening, affect these dynamics. Unlike prior research that primarily relied on supply-side data (e.g., Beck et al., 2008; Hannig & Jansen, 2010), this study employs the Global Findex database (demand-side), an overarching source on individual financial practices and decisions.

The structure of the paper is as follows: The pertinent literature is examined in Section 2, the methodology is outlined in Section 3, the results and findings are put forward in Section 4, and the policy impacts are addressed in Section 5.

2. Literature review

Key literature examining the interconnectedness of FinTech, financial inclusion, inequality, and factors influencing resource mobilization inform the current study.

Inequality and FinTech

Increased internet and mobile penetration in African nations have demonstrated improved access to FinTech and decreased inequality (Tchamyu, 2019; Kouladoum et al., 2022). Positive effects of this include escaping the poverty trap, building savings, promoting rural entrepreneurship, and influencing financial decisions made by households (Yang & Zhang, 2022; Ge et al., 2022; Dzator et al., 2023; Chen & Liu, 2023; Zheng & Ma, 2023; Sampat et al., 2024; Kumar & Ahuja, 2025). Automating public disbursements reduces administrative expenses and minimizes corruption, thereby freeing up resources for public welfare initiatives and reducing wealth inequality (Muralidharan et al., 2014; Munyegera & Matsumoto, 2016; Muralidharan et al., 2017). Fintech offers greater incentives to bridge the rural-urban divide and gender-based inequities stimulating female labour market participation (Cheng et al., 2021; Loko & Yang, 2022; Morgan, 2021). FinTech could render financial services readily available, especially to smaller firms. (Lahreche et al., 2020)

But studies propose the cautious and planned implementation of FinTech, as in certain contexts it can exacerbate income inequality (Li & Li, 2021). Also, Asongu & Odhiambo, (2019) and Kolovich & Newiak, (2024) emphasize that expanding information technology beyond basic levels is essential to alleviate inequality to increase female involvement in the economy. Some studies highlight the challenges of rising gender divide perpetuated by FinTech (Anandhita & Ariansyah, 2018). Therefore, from the foregoing discussion on FinTech and inequality, the resulting hypothesis is derived:

- H1: There is a significant link involving FinTech and inequality.

Financial inclusion and inequality

Mounting research findings suggest that a higher level of financial inclusion is connected with lower national inequality in income (Ozturk & Ullah, 2022; Das & Chatterjee, 2023). However, this dynamic is not uniform across the regions suggesting that while access and affordable financial offerings can mitigate income disparity, factors like type, nature and quality of institutions, maturity of markets, instruments, and policies could have different impact on this

relationship (Dabla-Norris et al., 2015; Markkanen & Anger-Kraavi, 2019; Banna et al., 2021; Choudhary & Thenmozhi, 2024; Park & Mercado, 2018; Le et al., 2019; Ozili, 2020).

Financial inclusion may be hindered by an ongoing gender inequality in adoption of technology in finance, as per Cheng et al. (2021). Studies reveal that women ownership of bank accounts is less than male ownership (Demirgüç-Kunt et al., 2020), women manage fewer household finances (Guiso & Zaccaria, 2023; Chen et al., 2023), or partake less in the equity market (Ke, 2017; Bucher-Koenen et al., 2024; McMahon & Reiche, 2024). There are gender variations in attitudes and preferences towards emerging financial technologies. However, as these emerging technologies become more widely adopted and governed by frameworks over time, the gender gap could potentially narrow (Cheng et al., 2021). Based off the foregoing discussion, the following hypotheses are derived.

- H2a. There is a significant link involving financial inclusion and inequality.
- H2b. There is a mediation effect of financial inclusion in the FinTech-inequality association.

FinTech and financial inclusion

Different fintech instruments for remittance, lending, payment, and credit risk evaluations have bolstered financial inclusion across various parts of the world (Ghosh, 2016; Okello Candiya Bongomin et al., 2018; Tchamyou et al., 2019; Lahreche et al., 2020; Click or tap here to enter text. Myovella et al., 2020; Asongu & Odhiambo, 2020; Hendricks & Mwapwele, 2024). This has presented an impetus meant for the expansion of digital access to banking and other financial offerings in a number of nations as per the latest Global Findex Survey results. There is strong evidence to suggest that households using mobile banking accounts are more inclined to possess formal bank accounts, remit funds, and save for the future (Morawczynski, 2009; Mbiti et al., 2011; Ghosh, 2016; Ouma et al., 2017; Lyons & Kass-Hanna, 2021; Cheng et al., 2021; Shaikh et al., 2023;). Additionally, it has been observed that mobile money benefits SMEs and entrepreneurial financial inclusion, enhancing resource mobilization by increasing availability of bank credit (Gosavi, 2018) Fintech frequently enhances traditional banking services rather than replacing them, as evidenced by (Fuster et al., 2019) Contrarily, it was proposed that Fintech and BigTech firms extend credit and financial support to borrowers who are often overlooked by traditional banks (Agarwal et al., 2019; (Berg et al., 2022; Hodula, 2022). Based on the above, the following hypothesis is framed.

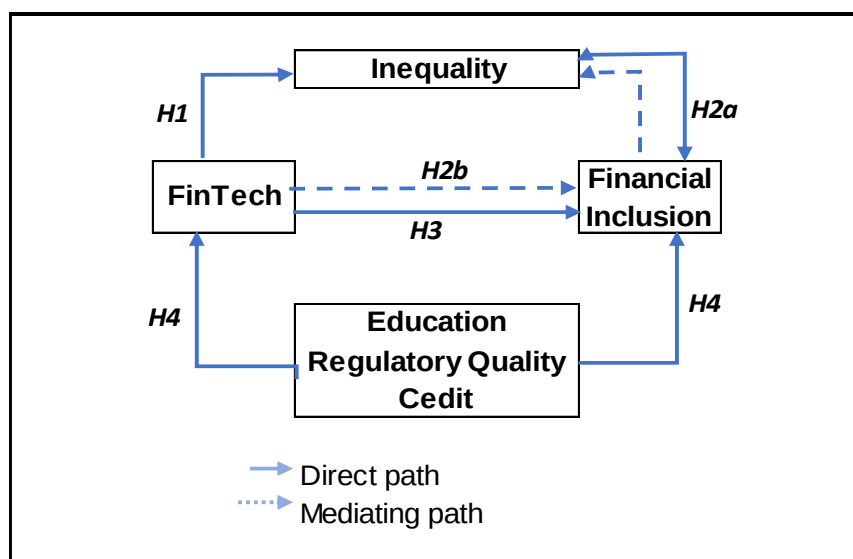
- H3: There is a significant link between FinTech and financial inclusion.

Key enablers for resource mobilizations

Digital financial inclusion can result in higher resource mobilization through efficiencies and innovation (Sharma, 2016; Becker, 2017; Chen et al., 2019). It aids in better distribution of resources through disintermediation and lower transaction costs. To sustain such benefits, regulations must evolve fostering education, invention, and consumer welfare (Arner et al., 2015; Anagnostopoulos, 2018) Buckley et al., 2020; Thakor, 2020; Hodson, 2021). An increasing number of studies indicate that education is crucial in promoting financial inclusion and overall well-being. Variation in financial awareness and knowledge influences heterogeneity in asset accumulation, susceptibility, and financial resilience (Lusardi & Mitchell, 2014; Goyal & Kumar, 2021; Lusardi et al., 2017) Increased pecuniary and technological literacy enables individuals to engage with FinTech more effectively (Aoun, 2017) Finally, financial deepening (captured by credit) combined with more equitable financial systems can reduce inequality while enhancing resource allocation (Dabla-Norris et al., 2015) To reduce inequality, expansion of financial services must be accompanied by greater financial inclusion. Consequently, in accordance with this discussion, the following hypothesis can be formulated.

- H4: Regulatory quality, education, and financial deepening significantly influence the FinTech-financial inclusion-inequality relationship.

Figure 1 illustrates the conceptual framework of the research.



3. Methodology

In this paper, we construct the digital and traditional financial inclusion index. The various indicators as presented in Appendix A. The following model specification was used to understand how FinTech impacts financial inclusion.

$$FI_{it} = c + \beta_1 X_{it} + \beta_2 Fintech_{it} + \alpha_i + \epsilon_{it} \dots \dots \dots (1)$$

where FI represents financial inclusion index (digital or traditional); ‘Xs’ are the controls and details are presented in Appendix A. The control variables were chosen following the literature in the preceding section.

Traditional and digital financial inclusion is estimated using the Principal Component Analysis (PCA), a popular method employed in several studies (Jolliffe & Cadima, 2016). The detailed methodology is discussed in Appendix B.

To assess how FinTech and financial inclusion affect dimensions of inequality, we propose the following model:

$$Inequality_{it} = c + \beta_1 X_{it} + \beta_2 Fintech_{it} + \beta_3 FI + \alpha_i + \epsilon_{it} \dots \dots \dots (2)$$

In this context, where inequality refers to gender inequality and income inequality, FinTech serves as proxy for technological advancement, FI represents financial inclusion, and X denotes the control variables. To mitigate potential endogeneity concerns, lagged values of these control variables are used.

However, regression analysis does not accommodate multiple dependent variables in a relationship. Therefore, to accurately model causative dynamics of the key variables, Structuring Equation Modelling (SEM) is applied. Appendix C contains an explanation of the rationale.

4. Results and findings

We conducted multiple regression analyses to establish the influence of financial technology on financial inclusion and on inequality as shown in Table 1 and 2 of Appendix D. In the next stage, we enhanced the model by combining financial inclusion indices as additional regressors, as presented in Table 1.

Digital financial inclusion substantially lowers the different inequality forms. Further, digital financial inclusion has decreased the coefficient value of FinTech (7.88 to 7.50) indicating that

the income inequality-inducing influence of FinTech reduces marginally when directed through digitally supported inclusion initiatives. It has raised the coefficient value of FinTech (-0.046 to -0.433) indicating that the gender inequality-reducing influence of FinTech increases when directed through digitally supported inclusion initiatives. Traditional financial inclusion significantly reduces income inequality. These results provide preliminary evidence that financial inclusion acts as a mediator between FinTech and inequality (income and gender). This suggests that financial inclusion is a principal mechanism as a primary pathway whereby FinTech affects inequality.

While we find preliminary evidence suggesting that financial technology and financial inclusion influence dimensions of inequality, the results do not accurately model causal mechanisms. Therefore, to better capture inter-relationships, we apply SEM. For ease of analysis in the SEM modelling, a composite index of financial inclusion (digital and traditional) is constructed by applying PCA.

Table 1: The impact of FinTech and financial inclusion on inequality

Explanatory variable	Gender Inequality	Income Inequality
FinTech	-0.433** (0.184)	7.50*** (2.91)
Digital Financial Inclusion	-0.058** (0.03)	-0.55* (0.59)
Traditional Financial Inclusion	-0.187 (0.137)	-5.89* (2.26)
Population growth	0.003 (0.01)	0.007 (0.014)
GDP per capita growth	-0.0004 (0.0005)	-0.008 (0.0014)
Education	-0.326 (0.033)	0.769 (0.727)
Regulatory quality	-0.57*** (0.131)	-9.05*** (2.76)
Credit/GDP	-0.24** (0.147)	-5.68* (2.18)
Constant	0.824 (0.084)	19.5 (1.70)
R-square	0.43	0.2

Robust standard errors in parentheses (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$)

4.1 FinTech-financial inclusion-income inequality relationship

The SEM analyses shown in Table 2 establishes a direct statically significant path from FinTech to income inequality with a positive coefficient ($\beta = 15.607$) contradicting expectations that

FinTech would lower income inequality (Altunbaş & Thornton, 2019) Additionally, a significant negative path from financial inclusion to income inequality was observed ($\beta = -23.717$) consistent with studies that suggest increased financial inclusion decreases income inequality (Park & Mercado Jr, 2018, Omar & Inaba, 2020).

The results show that a certain degree of income inequality can incentivize financial inclusion ($\beta = 0.016$) consistent with some studies (Lazear & Rosen, 1981; Barro, 2000). The SEM results show that FinTech increases financial inclusion ($\beta = 0.053$) supported by similar investigations (Tchamyu et al., 2019; Lahreche et al., 2020; Chowdhury & Chowdhury, 2024)

Factors like regulatory quality ($\beta=0.15$) and availability of credit ($\beta=0.1$) support the proliferation of FinTech (Dabla-Norris et al., 2015; Buckley et al., 2020; Hodson, 2021) Education ($\beta = 0.184$), regulatory quality ($\beta=0.614$) and credit ($\beta=0.227$) are significant in influencing financial inclusion.

The mediation analysis establishes that financial inclusion mediates the education impact, regulatory quality and credit on income disparity showing negative coefficient ($\beta = -2.925$, -8.714 , and -2.697 respectively) signaling that efficiencies in these factors can reduce income inequality. The model fits well as justified by a $\chi^2 = 10.998$ ($df=6$, $p=0.1$), $TLI = 0.954$, $CFI= 0.985$ and $RMSEA = 0.043$, all meeting recommended limits (Hu & Bentler, 1999; Kyriazos, 2018; Cheung et al., 2024)

Table 2: Direct and Indirect effects of SEM model

Variable	Direct effect	Hypothesis	Indirect effect	Hypothesis
FinTech				
Education	-0.022 (-0.018)	Not supported	0 (no path)	No path
Regulatory quality	0.156*** (0.029)	H4 supported	0 (no path)	
Credit	0.100*** (-0.034)	H4 supported	0 (no path)	
Financial Inclusion				
FinTech	0.053** (0.118)	H3 supported	0.000 (-0.001)	Not supported
Income inequality	0.016*** (0.003)	H2a supported	0 (-0.001)	
Education	0.184*** (0.042)	H4 supported	0.005 (-0.006)	
Regulatory quality	0.614*** (0.079)		-0.031 (-0.025)	
Credit	0.227*** (0.081)		-0.007 (-0.012)	
Income inequality				
FinTech	15.607*** (3.895)	H1 supported	-3.296 (2.301)	Not supported
Financial Inclusion	-23.71*** (3.335)	H2a supported	6.403 (2.481)	
Population growth	0.057 (0.032)	Not supported	0.015 (0.015)	
GDP per capita growth	-0.002 (0.003)		0.001 (0.001)	
Education	0 (no path)	No path	-2.925 *** (0.791)	H4 supported Mediation through Financial Inclusion
Regulatory quality	0 (no path)		-8.714*** (1.584)	
Credit	0 (no path)		-2.697** (1.481)	

Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$)

The FinTech-financial inclusion-income inequality nexus based on the SEM modelling is presented in Figure 2.

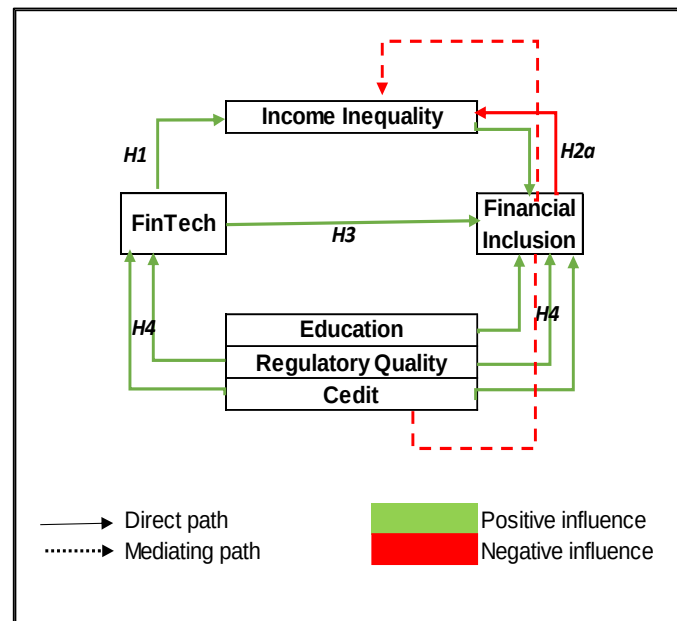


Figure 2: Conceptual model (FinTech-financial inclusion-income inequality)

4.2 FinTech-financial inclusion-gender inequality relationship

The SEM analysis shown in Table 3 found no meaningful statistical between FinTech and gender inequality. A significant negative path from financial inclusion to gender inequality was observed ($\beta = -1.036$) consistent with studies that suggest increased financial inclusion decreases gender inequality (Philippon, 2019; Carlin et al., 2019; Olafsson & Pagel, 2024; Agarwal et al., 2020; Bao & Huang, 2021; Boot et al., 2020; Gopal & Schnabl, 2020; Breza et al., 2020; Chen et al., 2023; Duan, 2025; Cumming et al., 2023).

The results show that certain degree of gender inequality can incentivize financial inclusion ($\beta = 3.045$) consistent with studies advocating for more financial access for women (Forge & Vu, 2020; Ndoya & Tsala, 2021). The SEM results show that FinTech increases financial inclusion ($\beta = 2.536$), and regulatory quality ($\beta = 0.159$) supports the proliferation of FinTech as seen in the previous case. Education ($\beta = 0.426$) and regulatory quality ($\beta = 2.817$) are significant in influencing financial inclusion (Bazarbash & Beaton, 2020).

The mediation analysis establishes that FinTech reduces gender inequality through financial inclusion ($\beta = -0.218$). The mediation analysis establish that financial inclusion mediates the influence of education and regulatory quality on gender disparity showing negative coefficient ($\beta = -0.823$ and $\beta = -0.138$ respectively) signaling that efficiencies in these factors can reduce gender inequality. The model

fits well as justified by a $\chi^2 = 13.5$ (df=6, p= p= 0.107), TLI = 0.969, CFI= 0.940 and RMSEA = 0.049, all meeting recommended limits (Hu & Bentler, 1999; Kyriazos, 2018; Cheung et al., 2024)

Table 3: Direct and Indirect effects of SEM model

Variable	Direct effect	Hypothesis	Indirect effect	Hypothesis	
FinTech					
Education	0.042 (0.035)	Not supported	0 (no path)	No path	
Regulatory quality	0.159** (0.075)	H4 supported	0 (no path)		
Credit	-0.114 (0.127)	Not supported	0 (no path)		
Financial Inclusion					
FinTech	2.536** (1.209)	H3 supported	2.326 (1.138)	Not supported	
Gender inequality	3.045** (1.392)	H2a supported	2.312 (1.352)		
Education	0.426** (0.220)	H4 supported	0.315 (0.199)		
Regulatory quality	2.817*** (1.155)		2.105 (1.139)		
Credit	-0.511 (0.692)	Not supported	0.364 (0.558)		
Gender inequality					
FinTech	-0.546 (0.336)	Not Supported	-0.218* (0.303)		H2b supported mediation through Financial Inclusion
Financial Inclusion	-1.036 *** (0.159)	H2a supported	0.786 (0.204)	Not supported	
Population growth	0.018 (0.006)	Not supported	0.015 (0.015)		
GDP per capita growth	0.001 (0.003)		0.001 (0.001)		
Education	0 (no path)	No path	-0.138 ** (0.046)	H4 supported Mediation through Financial Inclusion	
Regulatory quality	0 (no path)		-0.823 ** (0.108)		
Credit	0 (no path)		0.214 (0.177)		Not supported

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Based on the SEM modelling, the FinTech-financial inclusion-gender inequality nexus is presented in Figure 3.

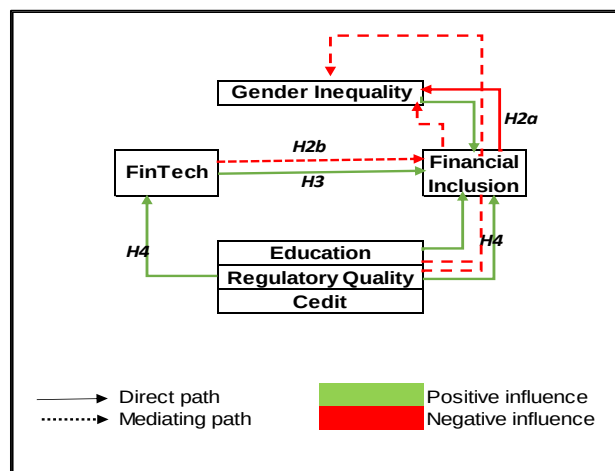


Figure 3: Conceptual Model (FinTech-financial inclusion-gender inequality)

5. Conclusion

This research developed a novel conceptual model and employed the SEM approach to investigate the interaction between inequality, financial technology, and financial inclusion across a panel of 113 national utilizing 2011-2021 Global Findex survey data. Our research offers a distinctive perspective by looking at the joint dynamics of these constructs to provide a comprehensive understanding of what factors reduce or exacerbate different dimensions of inequality.

We find that FinTech increases income inequality while decreasing gender inequality through financial inclusion. Although FinTech reduces search costs and improves advice for households and businesses, it does not diminish inequality across all categories. Financial inclusion is essential in reducing various forms of inequality. In fact, some income and gender disparities can incentivize the development and implementation of inclusive financial policies by providing safe and efficient financial options to disadvantaged individuals and communities. Regulatory quality, education, and access to credit contribute to reducing different forms of inequality by enhancing financial inclusion. These empirical results further underscore the role of key enabling factors in shaping the interplay of various facets.

The findings of our study have significant policy ramifications. First, to promote inclusive growth, policymakers must consider strategies to address different types of inequality. Our empirical findings show how FinTech, and financial inclusion may influence inequality through many channels and therefore, context-specific policies are needed. Second, access to appropriate financial offerings that benefit resource-constrained individuals and communities through targeted interventions should be a priority to reduce inequality. Third, our findings point to financial inclusion enabled by FinTech as a viable policy for lowering inequality. However, the same inequalities may expand in the future due to a lack of necessary infrastructure, geo-political tensions, lower awareness and trust, etc. Therefore, effective policymaking must balance the goals of ensuring stable growth and expanding inclusive policies, while fostering innovation and competition.

Appendix A: *Summary of variables*

Index / Variable	Indicators / Measures	Population Group
Digital Financial Inclusion Index	- Mobile cellular subscriptions - Internet access - Percentage of people with a mobile money account - Individuals who have made or received a digital payment - Individuals using a mobile phone or the internet to pay bills - Individuals checking account balances through a mobile phone or the internet	Individuals aged 15 and older
Traditional Financial Inclusion Index	- Number of commercial bank branches per 100,000 adults - Number of automated teller machines (ATMs) per 100,000 adults - Proportion of people with financial institution accounts - Ownership of credit/debit cards - Proportion of individuals with savings at a financial institution - Borrowing from a formal financial institution - Savings using a savings club or a person outside the family - Borrowing from family or friends	Individuals aged 15 and older
FinTech	- Mobile phone and fixed-line subscriptions	General population
Inequality Dimensions	- Gender inequality (Gender Inequality Index) - Income inequality (Average income of the top 10 percentile / Average income of the bottom 10 percentile)	General population

- Data sources:
 - The Global Financial Inclusion Database (Findex)
 - World Inequality Database for inequality,
 - World Development Indicators Database.
- Sample: 113 countries
- Time: 2011, 2014, 2017, and 2021.

Appendix B: *Principal Component Analysis (PCA) employed for indexing strategy*

Financial inclusion is difficult to quantify in a straightforward manner. However, the interaction of several causative variables is thought to determine this variable. Financial inclusion, we believe, demonstrates a latent structure that cannot be examined directly but can be inferred from other variables. In the estimation of any latent variable, two essential concerns arise: the selection of relevant variables and the assignment of weights. To get the most information out of a data set included in an index, the weights assigned to the indicators or sub-indices are

crucial. An effective composite index should incorporate meaningful information from all the indicators without giving disproportionate weight to any single one or group of them.

As an indexing technique, the current paper uses a two-stage principal components methodology to evaluate financial inclusion. One popular method for reducing a dataset's dimensionality is PCA by data extraction for hidden features and correlations, as well as deleting data with too much information. PCA, unlike other linear transformation methods, does not rely on fixed vectors (Taghizadeh-Hesary et al., 2019). Furthermore, (Yoshino & Taghizadeh-Hesary, 2016) found that PCA can discover the interrelationship between the multiple models constructed. PCA is a popular method for analyzing explanatory data. It displays the structure of the database and explains inconsistencies as a projection approach (Jolliffe & Cadima, 2016; Huang et al., 2021). PCA has been found to be suitable in the investigation of phenomena influenced by several financial variables. For example, Celestin, (2025) applied PCA to cryptocurrency portfolios and (Sai et al., 2025) used PCA to understand digital pattern trends, and

To determine the applicability of the data the following tests were run (Hair et.al., 2006; Tabachnick & Fidell, 2007; Hair et al., 2010; Tabachnick & Fidell, 2013).

Bartlett's test of sphericity	Test determines whether the correlation matrix used in the PCA is a significant identity matrix
Kaiser-Meyer-Olkin (KMO)	Test determine the sampling adequacy. The KMO index varies from 0 to 1, with values greater than 0.5 indicating that the analysis is appropriate.

We followed the methodologies of Sarma, (2008) and Cámara & Tuesta, (2014) to create the financial inclusion index. The dimensions for each sample of our financial inclusion index are calculated as-

$$X_{i,d} = \frac{x_i - m_i}{M_i - m_i} \dots\dots\dots(1)$$

- x_i represents the actual value of indicator i
- m_i the minimum value
- M_i the maximum value of dimension i
- $X_{i,d}$ The standardized value of indicator i within dimension

PCA is employed to aggregate each indicator to a dimension index

j^{th} eigenvalue	represented by the symbol λ_j ($j = 1, \dots, p$), where the subscript j stands for the total quantity of principal components, which is equivalent to the number of harmonized indicators, p
P_k ($k = 1, \dots, p$)	the k th principal component and suppose that $\lambda_1 > \lambda_2 > \dots > \lambda_p$

Each dimension index is then derived based on a weighted average of these components:

$$D_d = \frac{\sum_{j,k=1}^p \lambda_j P_k}{\sum_{j=1}^p \lambda_j} \dots \dots \dots (2)$$

D_d	dimension d index and $P_k = X\lambda_j$
λ_j	the weights and X is the matrix of harmonized indicators

Within each dimension, the biggest percentage of variance is captured by the first principal component. Once we have the dimension indices financial inclusion index is calculated as in Equation 2,

$$FI_i = \frac{\sum_{j=1}^p \lambda_j P_{ki}}{\sum_{j=1}^p \lambda_j} \dots \dots \dots (3)$$

FI_i	composite financial inclusion index for country i .
$P_k = X\lambda_j$	λ_j represents the dimension-specific weights and X is the dimensions matrix.

Equation 3 can be rewritten as follows

$$FI_i = w_1D_{1,i} + w_2D_{2,i} + w_3D_{3,i} + \dots w_kD_{ni} \dots \dots \dots (4)$$

w_k	weights obtained from PCA
D_i	represents the dimensions

Equation 4 presents that the financial inclusion index is a weighted average of individual components (Park & Mercado, 2021).

Appendix C: *Rationale for Structural Equation Modelling (SEM)*

SEM is a method that combines aspects of factor analysis and multiple regressions, allowing for concurrent assessment of interrelationships among the variables. The SEM approach is well suited to capturing the moderating effect through two effects. These comprise the indirect effect that is conveyed through a mediator as well as the direct effect that the exogenous variable has on the outcome.

According to Hair et al., (2010) full mediation is established when the direct influence of an exogenous variable on an outcome becomes non-significant upon the inclusion of the indirect path. Whereas partial mediation occurs when the direct effect remains significant but is reduced in magnitude. The model fit is evaluated using various indicators (Hankonen et al., 2010).

chi-square (χ^2) statistic and its degrees of freedom
Comparative Fit Index (CFI) or Tucker-Lewis index (TLI),
Root Mean Square Error of Approximation (RMSEA)

Mediation analysis is appropriate when no direct association is observed between two variables and a mediator mediates the inter-relationship ((Polizzi, 2025;Obagbuwa et al., 2021; Chinoda & Mashamba, 2021).

Appendix D: *Preliminary regression modelling*

We ran a panel regression with fixed effects to establish that FinTech proxy is statistically significant with traditional and digital financial inclusion aligning with emerging research as shown in Table 1 of Appendix D.

Table 1: The impact of FinTech on financial inclusion

Explanatory variables	Traditional Financial Inclusion	Digital Financial Inclusion
FinTech	0.182*** (0.06)	0.95*** (0.313)
Population growth	0.002*** (0.004)	0.003* (0.001)
GDP per capita growth	0.0003* (0.0046)	-0.002 (0.001)
Education	0.125*** (0.017)	0.295*** (0.067)
Regulatory quality	0.53*** (0.047)	0.703** (0.359)
Credit/GDP	0.184* (0.04)	-0.446* (0.241)
Constant	-0.145 (0.03)	-0.606 (0.212)

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 2 of Appendix D illustrates the regression results for gender and income inequality. The results indicate that FinTech increases income inequality and decreases gender inequality. Education significantly reduces income inequality, while robust regulatory quality in a country significantly reduces all dimensions of inequality. The results also indicate that the ratio of credit to GDP significantly reduces income inequality.

Table 2: The impact of FinTech on inequality

Explanatory variable	Gender Inequality	Income Inequality
FinTech	-0.046** (0.181)	7.88*** (2.87)
Population growth	0.0003 (0.002)	0.20 (0.28)
GDP per capita growth	-0.0004 (0.0005)	-0.001 (0.002)
Education	-0.60** (0.031)	0.03 (0.679)
Regulatory quality	-0.74*** (0.108)	-12.29*** (2.59)
Credit/GDP	0.196 (0.152)	-6.29*** (2.17)
Constant	0.56 (0.03)	20.58 (1.67)

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

References

- Agarwal, S., Qian, W., Ren, Y., Tsai, H.-T. T., & Yeung, B. Y. (2020). The Real Impact of FinTech: Evidence from Mobile Payment Technology. *SSRN Electronic Journal*.
- Agarwal, S., Qian, W., Yeung, B. Y., & Zou, X. (2019). Mobile Wallet and Entrepreneurial Growth. *AEA Papers and Proceedings*, 109, 48–53.

- Ali, A. E. R. A. M. H. H. F. (2022). Does Globalization Promote Financial Integration in South Asian Economies? Unveiling the Role of Monetary and Fiscal Performance in Internationalization. *MPRA Paper 115304, University Library of Munich, Germany*.
- Altunbaş, Y., & Thornton, J. (2019). The impact of financial development on income inequality: A quantile regression approach. *Economics Letters*, 175, 51–56.
- Anandhita, V. H., & Ariansyah, K. (2018). Gender Inequality on the Internet Access and Use in Indonesia: Evidence and Implications. *Proceeding - 2018 International Conference on ICT for Rural Development: Rural Development through ICT: Concept, Design, and Implication, IC-ICTRuDEv 2018*, 142–147.
- Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. *Journal of Economics and Business*, 100, 7–25.
- Aoun, J. E. (2017). Robot-Proof. *Robot-Proof*. <https://doi.org/10.7551/MITPRESS/11456.001.0001>
- Arner, D. W., Barberis, J. N., & Buckley, R. P. (2015). The Evolution of Fintech: A New Post-Crisis Paradigm? *SSRN Electronic Journal*.
- Asongu, S. A., & Odhiambo, N. M. (2019). How enhancing information and communication technology has affected inequality in Africa for sustainable development: An empirical investigation. *Sustainable Development*, 27(4), 647–656.
- Asongu, S. A., & Odhiambo, N. M. (2020). Foreign direct investment, information technology and economic growth dynamics in Sub-Saharan Africa. *Telecommunications Policy*, 44(1). <https://doi.org/10.1016/j.telpol.2019.101838>
- Azmeh, C. (2025). Bridging divides: the role of Fintech and financial inclusion in reducing poverty and inequality in developing countries. *Innovation and Development*.
- Barro, R. J. (2000). Inequality and growth in a panel of countries. *Journal of Economic Growth*, 5(1), 5–32.
- Banna, H., Hassan, M. K., & Rashid, M. (2021). Fintech-based financial inclusion and bank risk-taking: Evidence from OIC countries. *Journal of International Financial Markets, Institutions and Money*, 75, 101447.
- Bao, Z., & Huang, D. (2021). Shadow Banking in a Crisis: Evidence from Fintech During COVID-19. *Journal of Financial and Quantitative Analysis*, 56(7), 2320–2355
- Basu, S. and M. S. (2008). When does growth trickle down to the poor? The Indian case. *Cambridge Journal of Economics*, Vol. 32,(No. 3).
- Bazarbash, M., & Beaton, K. (2020). Filling the Gap. *IMF Working Papers*, 20(150).
- Beck, T., Demirgüç-Kunt, A., & Martinez Peria, M. S. (2008). Banking Services for Everyone? Barriers to Bank Access and Use around the World. *The World Bank Economic Review*, 22(3), 397–430.
- Becker, G. (2017). *Does FinTech Affect Household Saving Behavior? Findings from a Natural Field Experiment*.
- Berg, T., Fuster, A., & Puri, M. (2022). FinTech Lending. *Annual Review of Financial Economics*, 14(1), 187–207.
- Boot, A., Hoffmann, P., Laeven, L., & Ratnovski, L. (2020). *Financial intermediation and technology: What's old, what's new?*
- Breza, E., Kanz, M., & Klapper, L. F. (2020). Learning to Navigate a New Financial Technology: Evidence from Payroll Accounts. *SSRN Electronic Journal*.
- Bucher-Koenen, T., Alessie, R., Lusardi, A., & Rooij, M. van. (2024). Fearless Woman: Financial Literacy, Confidence, and Stock Market Participation.
- Buckley, R. P., Arner, D. W., Zetsche, D. A., & Weber, R. H. (2020). The road to RegTech: the (astonishing) example of the European Union. *Journal of Banking Regulation*, 21(1), 26–36.
- Cámara, N., & Tuesta, D. (2014). *Measuring Financial Inclusion: A Multidimensional Index Measuring Financial Inclusion: A Multidimensional Index Measuring Financial Inclusion: A Multidimensional Index*
- Carè, R., Boitan, I. A., Stoian, A. M., & Fatima, R. (2025). Exploring the landscape of financial inclusion through the lens of financial technologies: A review. *Finance Research Letters*, 72, 106500.
- Carlin, B., Olafsson, A., & Pagel, M. (2019). Generational Differences in Managing Personal Finances. *AEA Papers and Proceedings*, 109, 54–59.
- Celestin, Prof. Dr. M. (2025). Principal Component Analysis For Simplifying Multivariate Financial Data In Portfolio Risk Analysis. *SSRN Electronic Journal*.
- Chen, M. A., Wu, Q., & Yang, B. (2019). How Valuable Is FinTech Innovation? *The Review of Financial Studies*, 32(5), 2062–2106.
- Chen, S., Doerr, S., Frost, J., Gambacorta, L., & Shin, H. S. (2023). The fintech gender gap. *Journal of Financial Intermediation*, 54, 101026.
- Chen, K., & Liu, Y. (2023). The impact of environmental regulation on farmers' income: an empirical examination based on different sources of income. *Environmental Science and Pollution Research*, 30(46), 103244–103258.

- Cheng, C.-Y., Chien, M.-S., & Lee, C.-C. (2021). ICT diffusion, financial development, and economic growth: An international cross-country analysis. *Economic Modelling*, 94, 662–671.
- Cheung, G. W., CooperThomas, H. D., Lau, R. S., & Wang, L. C. (2024). Correction to: Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 785–787.
- Chinoda, T., & Mashamba, T. (2021). Fintech, financial inclusion and income inequality nexus in Africa. *Cogent Economics & Finance*, 9(1)
- Chowdhury, E. K., & Chowdhury, R. (2024). Role of Financial Inclusion in Human Development: Evidence from Bangladesh, India and Pakistan. *Journal of the Knowledge Economy*, 15(1), 3329–3354.
- Choudhary, P., & Thenmozhi, M. (2024). Fintech and financial sector: ADO analysis and future research agenda. *International Review of Financial Analysis*, 93, 103201.
- Cumming, D. J., Johan, S., & Reardon, R. S. (2023). *Global Fintech Trends and Their Impact on International Business: A Review*. SSRN.
- Cumming, D. J., Vanacker, T., & Zahra, S. A. (2021). Equity crowdfunding and governance: Toward an integrative model and research agenda. *Academy of Management Perspectives*, 35(1), 69–95.
- Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). *INEQUALITY: CAUSES AND CONSEQUENCES INTERNATIONAL MONETARY FUND 1 Causes and Consequences of Income Inequality: A Global Perspective INTERNATIONAL MONETARY FUND*.
- Danladi, S., Prasad, M. S. V., Modibbo, U. M., Ahmadi, S. A., & Ghasemi, P. (2023). Attaining Sustainable Development Goals through Financial Inclusion: Exploring Collaborative Approaches to Fintech Adoption in Developing Economies. *Sustainability*, 15(17), 13039.
- Das, S., & Chatterjee, A. (2023). Impacts of ICT and digital finance on poverty and income inequality: a sub-national study from India. *Information Technology for Development*, 29(2–3), 378–405.
- Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2022). Fintech, financial inclusion and income inequality: a quantile regression approach. *The European Journal of Finance*, 28(1), 86–107.
- Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2020). The Global Findex Database 2017: Measuring Financial Inclusion and Opportunities to Expand Access to and Use of Financial Services. *The World Bank Economic Review*, 34(Supplement_1), S2–S8.
- Duan, C. (2025). Discovering current trends and forecasting future research directions in FinTech by way of co-word-burst analyses. *Industrial Management & Data Systems*, 125(2), 458–482.
- Dzator, J., Acheampong, A. O., Appiah-Otoo, I., & Dzator, M. (2023). Leveraging Digital Technology for Development: Does ICT Contribute to Poverty Reduction? *Telecommunications Policy*, 47(4), 1–34.
- Ediagbonya, V., & Tioluwani, C. (2022). The role of fintech in driving financial inclusion in developing and emerging markets: issues, challenges and prospects. *Technological Sustainability*, 2(1), 100–119.
- Ferilli, G. B., Palmieri, E., Miani, S., & Stefanelli, V. (2024). The impact of FinTech innovation on digital financial literacy in Europe: Insights from the banking industry. *Research in International Business and Finance*, 69, 102218.
- Forge, S., & Vu, K. (2020). Forming a 5G strategy for developing countries: A note for policy makers. *Telecommunications Policy*, 44(7), 101975.
- Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The Role of Technology in Mortgage Lending. *The Review of Financial Studies*, 32(5), 1854–1899.
- Ge, H., Tang, L., Zhou, X., Tang, D., & Boamah, V. (2022). Research on the Effect of Rural Inclusive Financial Ecological Environment on Rural Household Income in China. *International Journal of Environmental Research and Public Health*, 19(4), 2486.
- Ghosh, S. (2016). Does mobile telephony spur growth? Evidence from Indian states. *Telecommunications Policy*, 40(10–11), 1020–1031.
- Gomes, S., Lopes, J. M., & Ferreira, L. (2022). The impact of the digital economy on economic growth: The case of OECD countries. *Revista de Administracao Mackenzie*, 23(6).
- Gopal, M., & Schnabl, P. (2020). The Rise of Finance Companies and FinTech Lenders in Small Business Lending. *SSRN Electronic Journal*. <https://doi.org/10.2139/SSRN.3600068>
- Gosavi, A. (2018). Can Mobile Money Help Firms Mitigate the Problem of Access to Finance in Eastern sub-Saharan Africa? *Journal of African Business*, 19(3), 343–360.
- Goyal, K., & Kumar, S. (2021). Financial literacy: A systematic review and bibliometric analysis. *International Journal of Consumer Studies*, 45(1), 80–105.
- Guiso, L., & Zaccaria, L. (2023). From patriarchy to partnership: Gender equality and household finance. *Journal of Financial Economics*, 147(3), 573–595.
- Hair, J. F., B. W. C., B. B. J. and A. R. E. (2010). (2010). *Multivariate Data Analysis. 7th Edition*.
- Hair, J. F.; B. B. B. B. A. R. (2006). *Multivariate Data Analysis (6th Edition) 6th (sixth) Edition*.
- Hankonen, N., Absetz, P., Ghisletta, P., Renner, B., & Uutela, A. (2010). Gender differences in social cognitive determinants of exercise adoption. *Psychology & Health*, 25(1), 55–69.

- Hannig, A., & Jansen, S. (2010). Financial Inclusion and Financial Stability: Current Policy Issues. *SSRN Electronic Journal*.
- Hendricks, S., & Mwapwele, S. D. (2024). A systematic literature review on the factors influencing e-commerce adoption in developing countries. *Data and Information Management*, 8(1).
- Hodson, D. (2021). BIROn-Birkbeck Institutional Research Online The Politics of FinTech: Technology, Regulation and Disruption in UK and German Retail Banking. *Public Administration*, 99(4).
- Hodula, M. (2022). Does Fintech credit substitute for traditional credit? Evidence from 78 countries. *Finance Research Letters*, 46, 102469.
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.
- Huang, R., Ma, C., Ma, J., Huangfu, X., & He, Q. (2021). Machine learning in natural and engineered water systems. *Water Research*, 205.
- Jena, R. K. (2025). Factors Influencing the Adoption of FinTech for the Enhancement of Financial Inclusion in Rural India Using a Mixed Methods Approach. *Journal of Risk and Financial Management*, 18(3).
- Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2065), 20150202.
- Ke, D. (2017). Who Wears the Pants? Gender Identity Norms and Intra-Household Financial Decision Making. *SSRN Electronic Journal*.
- Kolovich, Lisa., & Newiak, Monique. (2024). *Gender equality and economic development in Sub-Saharan Africa*. International Monetary Fund.
- Kouladoun, J. C., Wirajing, M. A. K., & Nchofoung, T. N. (2022). Digital technologies and financial inclusion in Sub-Saharan Africa. *Telecommunications Policy*, 46(9).
- Kumar, J., & Ahuja, A. (2025). Journey of financial inclusion: a systematic literature review and conceptual framework for future research. *Asia-Pacific Journal of Business Administration*, 17(3), 632–656.
- Kyriazos, T. A. (2018). Applied Psychometrics: Sample Size and Sample Power Considerations in Factor Analysis (EFA, CFA) and SEM in General. *Psychology*, 9(8), 2207–2230.
- Lahreche, A., Ogawa, S., Beaton, K., Khera, P., Bazarbash, M., von Allmen, U., & Sahay, R. (2020). The Promise of Fintech. *Departmental Papers*, 2020(009), 1. <https://doi.org/10.5089/9781513512242.087>
- Lazear, E. P., & Rosen, S. (1981). Rank-Order Tournaments as Optimum Labor Contracts. *Journal of Political Economy*, 89(5), 841–864.
- Le, T. H., Chuc, A. T., & Taghizadeh-Hesary, F. (2019). Financial inclusion and its impact on financial efficiency and sustainability: Empirical evidence from Asia. *Borsa Istanbul Review*, 19(4), 310–322.
- Li, S., & Li, Y. (2021). *The Impact of Mobile Phone Adoption on Income Inequality*.
- Loko, B., & Yang, Y. (2022). Fintech, Female Employment, and Gender Inequality. *IMF Working Papers*, 2022(108), 1.
- Lusardi, A., Michaud, P.-C., & Mitchell, O. S. (2017). Optimal Financial Knowledge and Wealth Inequality. *Journal of Political Economy*, 125(2), 431–477.
- Lusardi, A., & Mitchell, O. S. (2014). The Economic Importance of Financial Literacy: Theory and Evidence. *Journal of Economic Literature*, 52(1), 5–44.
- Lyons, A. C., & Kass-Hanna, J. (2021). A methodological overview to defining and measuring “digital” financial literacy. *Financial Planning Review*, 4(2), e1113.
- Markkanen, S., & Anger-Kraavi, A. (2019). Social impacts of climate change mitigation policies and their implications for inequality. *Climate Policy*, 19(7), 827–844.
- Mbiti, I., Weil, D. N., Dinkelman, T., Driscoll, J., Eijkman, F., Habyarimana, J., Mwaura, S., Ndulu, B., Vaughn, P., & Yang, D. (2011). *NBER WORKING PAPER SERIES MOBILE BANKING: THE IMPACT OF M-PESA IN KENYA*.
- McMahon, M., & Reiche, L. (2024). DOES THE BANK OF ENGLAND NEED GENDERED COMMUNICATION? *National Institute Economic Review*, 269, 29–46.
- Morawczynski, O. (2009). Exploring the usage and impact of “transformational” mobile financial services: The case of M-PESA in Kenya. *Journal of Eastern African Studies*, 3(3), 509–525.
- Morgan, P. J. (2021). Fintech, financial literacy, and financial education. *The Routledge Handbook of Financial Literacy*, 239–258.
- Munyegera, G. K., & Matsumoto, T. (2016). Mobile Money, Remittances, and Household Welfare: Panel Evidence from Rural Uganda. *World Development*, 79, 127–137.
- Muralidharan, K., Das, J., Holla, A., & Mohpal, A. (2017). The fiscal cost of weak governance: Evidence from teacher absence in India. *Journal of Public Economics*, 145, 116–135.
- Muralidharan, K., Niehaus, P., & Sukhtankar, S. (2014). *NBER WORKING PAPER SERIES PAYMENTS INFRASTRUCTURE AND THE PERFORMANCE OF PUBLIC PROGRAMS: EVIDENCE FROM*

- BIOMETRIC SMARTCARDS IN INDIA Payments Infrastructure and the Performance of Public Programs: Evidence from Biometric Smartcards in India.*
- Murinde, V. (2012). Financial Development and Economic Growth: Global and African Evidence. *Journal of African Economies*, 21(suppl 1), i10–i56.
- Myovella, G., Karacuka, M., & Haucap, J. (2020). Digitalization and economic growth: A comparative analysis of Sub-Saharan Africa and OECD economies. *Telecommunications Policy*, 44(2), 101856.
- Ndoya, H. H., & Tsala, C. O. (2021). What drive gender gap in financial inclusion? Evidence from Cameroon. *African Development Review*, 33(4), 674–687.
- Nguyen, C. P., & Nasir, M. A. (2021). An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. *Energy Economics*, 99, 105289.
- Obagbuwa, O., Akande, J. O., & Tewari, D. (2021). **Acquired Financial Knowledge and Attitudes of South African University Students And Their Financial Decisions.** *The Journal of Accounting and Management*, 1(11), 96–110.
- Okello Candiya Bongomin, G., Ntayi, J. M., Munene, J. C., & Malinga, C. A. (2018). Mobile Money and Financial Inclusion in Sub-Saharan Africa: the Moderating Role of Social Networks. *Journal of African Business*, 19(3), 361–384.
- Olafsson, A., & Pagel, M. (2024). Retirement puzzles: New evidence from personal finances. *Journal of Public Economics*, 234, 105103.
- Omar, M. A., & Inaba, K. (2020). Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis. *Journal of Economic Structures*, 9(1), 1–25.
- Ouma, S. A., Odongo, T. M., & Were, M. (2017). Mobile financial services and financial inclusion: Is it a boon for savings mobilization? *Review of Development Finance*, 7(1), 29–35.
- Ozili, P. K. (2021, October). Financial inclusion research around the world: A review. In *Forum for social economics* (Vol. 50, No. 4, pp. 457–479). Routledge.
- Ozturk, I., & Ullah, S. (2022). Does digital financial inclusion matter for economic growth and environmental sustainability in OBRI economies? An empirical analysis. *Resources, Conservation and Recycling*, 185, 106489.
- Park, C. Y., & Mercado, R. (2018). Financial Inclusion, Poverty, And Income Inequality. *The Singapore Economic Review (SER)*, 63(01), 185–206.
- Park, C.-Y., & Mercado Jr, R. (2018). *Financial Inclusion* (0 ed., ADB Economics Working Paper Series). Asian Development Bank.
- Park, C.-Y., & Mercado, R. V. (2021). Financial inclusion : New measurement and cross-country impact assessment 1. *Financial Inclusion in Asia and Beyond*, 98–128. <https://doi.org/10.4324/9781003035916-4>
- Philippon, T. (2019). *NBER WORKING PAPER SERIES ON FINTECH AND FINANCIAL INCLUSION*. <http://www.nber.org/papers/w26330>
- Polizzi, S. (2025). Counterfactual Approach for Sequential Mediators in Mediation Analysis: A Suitable Methodological Approach for the Banking and Finance Literature? *Handbook of Financial Econometrics, Statistics, Technology, and Risk Management*, 4247–4267.
- Pradhan, R. P., Arvin, M. B., Nair, M. S., Hall, J. H., & Bennett, S. E. (2021). Sustainable economic development in India: The dynamics between financial inclusion, ICT development, and economic growth. *Technological Forecasting and Social Change*, 169.
- Sahay, R., Cihak, M., N'Diaye, P., Barajas, A., Mitra, S., Kyobe, A., Mooi, Y., & Yousefi, R. (2015). Financial Inclusion: Can it Meet Multiple Macroeconomic Goals? *Staff Discussion Notes*, 15(17), 1.
- Sai, V. G. S., Rajeev, R. H., Bharath, S., & Rajayya, A. (2025). Principal Component Analysis of Financial Inclusion Parameters: Insights into Digital Payment Index Trends. *Studies in Systems, Decision and Control*, 236, 179–188.
- Sampat, B., Mogaji, E., & Nguyen, N. P. (n.d.). *The Dark Side of FinTech in Financial Services: A Qualitative Enquiry into FinTech Developers' Perspective*.
- Sampat, B., Mogaji, E., & Nguyen, N. P. (2024). The dark side of FinTech in financial services: a qualitative enquiry into FinTech developers' perspective. *International Journal of Bank Marketing*, 42(1), 38–65.
- Sarma, M. (2008). *Index of Financial Inclusion*. <https://www.econstor.eu/handle/10419/176233>
- Shaikh, A. A., Alamoudi, H., Alharthi, M., & Glavee-Geo, R. (n.d.). *Advances in mobile financial services: a review of the literature and future research directions*. <https://doi.org/10.1108/IJBM-06-2021-0230>
- Sharma, D. (2016). Nexus between financial inclusion and economic growth: Evidence from the emerging Indian economy. *Journal of Financial Economic Policy*, 8(1), 13–36.
- Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics* (5th ed.). Allyn and Bacon.
- Tabachnick, B. G., & Fidell, L. S. (2013). *Using Multivariate Statistics* (6th ed.). Pearson.
- Taghizadeh-Hesary, F., Yoshino, N., Kim, C. J., & Mortha, A. (2019). A Comprehensive Evaluation Framework on the Economic Performance of State-Owned Enterprises. *SSRN Electronic Journal*.

- Tchamyou, V. S., Erreygers, G., & Cassimon, D. (2019). Inequality, ICT and financial access in Africa. *Technological Forecasting and Social Change*, 139, 169–184.
- Tchamyou, V. S. (2019). The Role of Information Sharing in Modulating the Effect of Financial Access on Inequality. *Journal of African Business*, 20(3), 317–338. <https://doi.org/10.1080/15228916.2019.1584262>
- Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833.
- Yang, T., & Zhang, X. (2022). FinTech adoption and financial inclusion: Evidence from household consumption in China. *Journal of Banking & Finance*, 145, 106668.
- Yoshino, N., & Taghizadeh-Hesary, F. (2016). *ADB Working Paper Series Major Challenges Facing Small and Medium-sized Enterprises in Asia and Solutions for Mitigating Them Asian Development Bank Institute*. <http://www.adb.org/publications/major->
- Zheng, H., & Ma, W. (2023). Impact of agricultural commercialization on dietary diversity and vulnerability to poverty: Insights from Chinese rural households. *Economic Analysis and Policy*, 80, 558–569.



Drivers of Debt-Financing and Related Sustainability Costs: A Pre-and Post GST Perspective of Indian Consumer Goods SMES

Sayak Mitra^a

^a Department of Management Studies, St. Xavier's College (Autonomous), Kolkata

Abstract

This study investigates how the sustainability costs, i.e. tax compliance, logistics, and digitisation costs, moderate with key determinants of debt financing, viz., profitability, liquidity, growth, business risk, and cash flow, to shape the debt financing of Indian consumer goods SMEs across pre- and post-GST periods. Data have been analysed using a short panel of 65 BSE-listed SMEs (selected under revised MSMED Act, 2025 thresholds) during 2014–2024. Arellano–Bond, 1991 dynamic estimation is applied to address issues like endogeneity and firm heterogeneity. Finally, study results exhibit a marked shift in the post-GST period. Profitability derogates long-term debt, while business risk becomes restrictive. However, sustainability factors moderate these effects differently, reflecting a lower compliance costs, improved logistics, and evolving digitisation, indicating that GST reforms and sustainable cost management are reshaping SMEs' debt financing strategies towards a sustainable future.

Keywords: GST implementation, Debt financing, Sustainability Cost, Moderation effect, Consumer Goods SME

1. Introduction

In the earlier tax regime, small-scale manufacturing firms used to pay multiple indirect taxes such as Excise, VAT, and Service Tax, amounting to nearly 25%. Post-GST implementation in July 2017, the indirect tax rate reduced to around 18% (Costea, [2021](#)) creating a unified "One Nation One Tax" structure. This reform eliminated tax disparities and cascading effects, difficulty and disparities owing to local VAT and state-specific tax laws while operating across regions, and digital compliance enhanced transparency, enabling manufacturing SMEs in the consumer goods sector to achieve stability and competitiveness. Furthermore, business development now depends significantly on sustainable debt policies and several financial planning costs (e.g. tax compliance, logistics and digitisation costs). These factors play a moderating role in shaping the interrelationship between debt policy determinants and capital structure strategies (Chen and Pohlschmidt 2025, 10). Furthermore, in alignment with the global shift towards sustainable business practices, the study highlights three sustainability dimensions that have significantly influenced SMEs across both periods. Firstly, *Tax Compliance Costs* have reduced under a unified GST framework, encouraging streamlined and sustainable practices (Vishnuhadevi and Bindu 2022, 10). Second, *Logistics costs* reduced in post-GST, due to the elimination of multiple inter-state checkpoints and regional levies, simplifying distribution networks (Clear tax 2025). Lastly, *Digitisation Costs* increased owing to the full-scale digitalization of tax compliance through the GSTIN portal. Enhanced transparency, better utilization of input tax credits, and the adoption of ERP systems by SMEs not only aided regulatory compliance but also promoted sustainable governance (PIB, Govt. of India 2025).

This study seeks to explore how select determinants of debt capital financing affect SMEs' debt procurement policies, specifically focusing on listed consumer goods manufacturers on the BSE (Rahman Asma, Rina Abdul and Noor et al. 2021, 70). This study collectively underscore how GST has revamped the structure decisions while aligning SMEs with sustainable growth pathways. Hence, the causal effects of debt policy determinants and capital structure planning, alongside the moderating impact of sustainable operating costs on the changing relationship between the pre- and post-GST regimes (Becker, Annette, Serena Fatica, and Michela Rancan 2025, 110) sets the main central theme of the study.

2. Review of Literature and Study variables

Firstly, this study examines firm-level determinants of debt policy in Consumer goods SMEs, focusing on profitability, liquidity, growth, business risk, and cash flow. (Eldomiaty, Tarek I. 2008, 30; Degryse, Hans, Peter De Goeij, and Peter Kappert 2012, 440; Hsiao, J., C. Hsu, and K. Hsu 2009, 250). Profitability, Liquidity, Business risk and strong cash flows reduce reliance on debt as because all of these determinants empowers firms with more internal funds (López-Gracia, José, and Francisco Sogorb-Mira 2008, 120; Mateev, Miroslav, Panikkos Poutziouris, and Konstantin Ivanov 2013, 30; Mitra, Sayak 2022; Mitra, Sayak, and Pradip Kumar Samanta. 2022, 40) while Sales growth rate shapes preferences of Long-term (for fund expansion) and Short-term borrowing (for working capital needs) (Almendros, Jose A. Clemente, and Francisco Sogorb Mira 2018, 170; Rao, Purnima, Satish Kumar, and Vinodh Madhavan 2019, 40; Mitra, Sayak, Rupa Mondal, and Saurav Mukherjee 2023, 30)

Tax compliance and digitization costs primarily encourage long-term debt usage due to their strategic, ongoing nature and potential for creating sustainable competitive advantages. However, it may increase short-term borrowing needs during peak compliance periods owing to working capital requirements and seasonal payment cycles (Bruce-Twum, Ernest and Danie Schutte 2021, 10). Furthermore, Logistics costs may discourage long-term debt due to their operational volatility and impact on predictable cash flows; Costea, [2021](#)). Nevertheless, Digitization costs generally favour long-term financing structures but may require short-term bridge financing during implementation phases (Kusumawardhani, Fieryanti Kamaril, Dwi Ratmono, et al. 2024,1111-1116).

Secondly, this paper captures the moderation effects of several Sustainability costs (Chen and Pohlschmidt 2025, 10) which are associated with the above select determinants of debt policy of SMEs. The increase in tax compliance costs amplify profitability, sales growth, and reduces business risk which in turn positive impact on debt, while deepening liquidity's negative has an effect. Cash flow shows a mixed influence, reducing debt need when strong but increasing reliance on debt when weak. Higher logistics costs weaken the profitability, liquidity that discourages debt, (Pohit Sanjib, Devendra B. Gupta, and Devender Pratap et al. 2019, 260) however, it strengthen the impact of sales growth and business risk on debt usage. Cash flow effects remain mixed due to seasonal cost surges and volatility in operational cycles. Digitization costs enhance the positive impact of profitability, liquidity, sales growth, and business risk on debt, as firms leverage financing to fund digital transformation. Cash flow effects are mixed, with initial debt-funded investments offset by long-term efficiency gains.

Table:1 Description of Variables

<i>Variable Type</i>	<i>Name of Variable</i>	<i>Description</i>	<i>Hypnotised effect</i>
Dependent Variables	Long Term Debt Ratio (LTDR)	Long-term borrowings excluding current options/ Total Assets	
	Short Term Debt Ratio (STDR)	Short-term borrowings excluding current options/ Total Assets	
Independent Variables	Profitability (PROF)	Earnings before Depreciation, Interest & Tax/ Total Assets	Negative
	Liquidity (LIQ)	Current Asset/ Current Liabilities excluding provisions	Negative
	Growth Rate (GROW)	$[\text{Total Sales}_t - \text{Total Sales}_{t-1}] / \text{Total Sales}_{t-1}$	Negative /Positive
	Business Risk (BR)	σ Earnings before Interest & Tax/ Total Assets	Negative
	Cash Flow (CF)	Profit after Tax + Depreciation & Amortisation/ Total Assets	Negative /Positive
Moderating Variables	Tax Compliance Cost (TCC)	Total payment of indirect tax (<i>incl. penalties, fines etc.</i>)/ Total Sales	Positive
	Logistics Cost (LC)	(Total distribution expenses + travelling expenses)/ Total Sales	Negative
	Digitisation Cost (DC)	(Depreciation on Software + software & other IT and digital connectivity charges)/ Total Sales	Negative
Control Variables	Size of Firm (SIZE)	Log of the Total Assets of firm	

3. Methodology

3.1 Data source and Sample

For the study, data has been extracted from the authorised database of PROWESS-CMIE, a sample of consumer goods manufacturing companies listed on the Bombay Stock Exchange (BSE). The study's sample selection involved several steps. Companies without complete data or those reporting negative reserves and surpluses (i.e., negative sales profitability) during the study period were excluded from the analysis. The selection further fathoms the revised thresholds under the Micro, Small, and Medium Enterprises Development (MSMED) Act, 2006, effective from April 1, 2025. According to the revised MSMED Act, eligible Small and Medium Enterprises must have an investment in plant and machinery of Rs. 2.5 crore to Rs.

125 crore, and turnover between Rs. 10 crore and Rs. 500 crore. Only firms consistently meeting these criteria from 2014 to 2024 were considered. After extensive screening, including data completeness and outlier removal, a final sample of 65 companies that fulfilled the SME criteria was selected.

3.2 Empirical Framework

Study's empirical framework is based on panel data methodology, specifically a short panel with greater number of cross-sectional units (65 companies) than time periods (11 years). The firm-level determinants of debt financing regressed as independent variables, while, "Tax Compliance Cost," "Logistics Cost," and "Digitisation Cost", are included in the model as moderating variables.). This analysis includes a comparative element based on GST implementation, represented by a dummy variable coded "0" before (April 2014 - March 2018) and "1" after implementation (April 2019 - March 2024) (Banerjee, Arindam, and Anupam De 2015, 180) Then these variables and the GST dummy are interacted by multiplying the raw variables with the dummy to create before-and-after transformed variables. Subsequently, moderation effects combined with the GST dummy are tested simultaneously in the regression model. Finally, multiple regression uses these moderated and GST-transformed variables, regressed against the dependent variables (i.e., long-term or short-term debt) in respective models, to capture the differential impact of GST implementation alongside moderating cost factors. This approach allows examination of the moderating effects of specific sustainable costs and the differential impact of GST implementation on debt financing decisions in SMEs through robust panel data analysis.

Initially,

Model framework-

$$Y_{it} = \alpha + \beta_1 * RV_{it} + \varepsilon_{it} \dots \dots (1)$$

Where, Y= dependent variable; RV= Regressor Variable; ε_{it} = Error term

Actual model with variables,

$$DR_{it} = \alpha + \beta_1 * PROF_{it} + \beta_2 * LIQ + \beta_3 * GROW_{it} + \beta_4 BR_{it} + \beta_5 * CF_{it} + \varepsilon_{it} \dots (1.1)$$

(Where, DR= Long Term Debt Ratio (LTDR)/ Short Term Debt Ratio; ε_{it} = error terms; α = intercept; β_i = Regressor co – efficient, $i = 1, 2, \dots, 5$)

Now, incorporating the moderating variables in the above (1) the revised model

Model framework-

$$Y_{it} = \alpha + \beta_1 * RV_{it} + \gamma * M_{it} + \varepsilon_{it} \dots \dots (2)$$

Where, Y= dependent variable; RV= Regressor Variable; M_{it} = Moderating variable; ε_{it} = Error term.

Actual model with variables,

$$DR_{it} = \alpha + \beta_1 * PROF_{it} + \beta_2 * LIQ + \beta_3 * GROW_{it} + \beta_4 * BR_{it} + \beta_5 * CF_{it} + \gamma * M_{it} + \varepsilon_{it} \dots (2.1)$$

(Where, Moderating variables (M_{it}) = “TCC”, “LC” and “DC”, use separately with each regressor in the model;

Now, introducing pre and post GST dummy (i.e. “0” and “1”) in the above (2) model we get,

$$Y_{it} = \alpha + \beta_i * D_RV_{it} + \gamma * M_{it} + \varepsilon_{it} \dots (3)$$

Actual model with variables,

Before implementation dummy [D = 1, otherwise, 0 (*where, “1” will be assigned for the year 2014 to 2018, beyond that is “0”*)] in the above (3) model

$$DR_{it} = \alpha + \beta_1 * D_{1,0} * PROF_{it} + \beta_2 * D_{1,0} * LIQ + \beta_3 * D_{1,0} * GROW_{it} + \beta_4 * D_{1,0} * BR_{it} + \beta_5 * D_{1,0} * CF_{it} + D_{1,0} * \gamma * M_{it} + \varepsilon_{it} \dots (3.1)$$

After implementation dummy [D = 1, otherwise, 0 (*where, “1” will be assigned for the year 2019 to 2024, previously that is “0”*)] in the above (3) model

$$DR_{it} = \alpha + \beta_1 * D_{0,1} * PROF_{it} + \beta_2 * D_{0,1} * LIQ + \beta_3 * D_{0,1} * GROW_{it} + \beta_4 * D_{0,1} * BR_{it} + \beta_5 * D_{0,1} * CF_{it} + D_{0,1} * \gamma * M_{it} + \varepsilon_{it} \dots (3.2)$$

The Dynamic panel regression is used here to apprehend the “change in impact” of regime switch in indirect tax regulation in the analysis. To be more specific, to investigate the effects in the model, Two-step Arellano-Bond dynamic panel-data estimation model has been employed. The Arellano–Bond, 1991 (Arellano, Manuel, and Stephen Bond 1991, 280) model corrects endogeneity by differencing regressors and eliminates omitted-variable bias through removing individual fixed effects. It instruments lagged dependent variables with past values. Moreover, the model robustness is assessed using Sargan and Hansen tests for instrument validity, autoregression diagnostics, and overall model fit, consistent with (Roodman, David 2009, 140); Baltagi, Badi Hani 2008)

4. Results and Discussion

The analysis highlights significant changes in determinants of firms' debt structures between pre- and post-GST periods in the Indian SME consumer goods sector, reflecting broad shifts in financial dynamics and moderation effects of certain sustainability costs.

From analysis it is evident that all components of descriptive statistics are under tolerable limit. So, data can be further analysed. Furthermore, all variables are found unlikely to have unit roots as specified under “Augmented dickey fuller test (fisher type) by (Mushtaq, Rizwan. 2021).

Table: 2 Correlation Matrix of all Study Variables

	LTDR	STDR	PROF	LIQ	GROW	BR	CF	TCC	LC	DC	SIZE	VIF
LTDR	1.000	-0.120	0.114	-0.115	0.039	-0.017	0.070	0.141	0.097	-0.027	-0.169	-
STDR	-0.120	1.000	-0.372	-0.449	0.020	0.035	-0.514	-0.057	-0.066	0.039	-0.176	-
PROF	-0.114	-0.372	1.000	0.226	0.009	0.144	0.929	0.079	0.062	-0.049	-0.086	8.18
LIQ	-0.115	-0.449	0.226	1.000	0.008	-0.015	0.276	0.002	0.054	0.006	0.096	1.12
GROW	0.039	0.020	0.009	0.008	1.000	-0.025	0.031	0.016	-0.056	-0.083	0.054	1.10
BR	-0.017	0.035	0.144	-0.015	-0.025	1.000	0.156	0.069	-0.024	-0.009	-0.299	1.26
CF	0.070	-0.514	0.929	0.276	0.031	0.156	1.000	0.057	0.022	-0.067	0.025	8.28
IDTL	0.141	-0.057	0.079	0.002	0.016	0.069	0.057	1.000	0.382	0.327	-0.066	1.23
LC	0.097	-0.066	0.062	0.054	-0.056	-0.024	0.022	0.382	1.000	0.578	0.027	4.03
DC	-0.027	0.039	-0.049	0.006	-0.083	-0.009	-0.067	0.327	0.578	1.000	-0.015	3.78
SIZE	-0.169	-0.176	-0.086	0.096	0.054	-0.299	0.025	-0.066	0.027	-0.015	1.000	1.42

Source(s): Authors Own Compilation.

From, Table-2, the nature of relationship between the dependent and independent variables are obtained. Furthermore, the correlation matrix shows no severe multicollinearity except between independent variables. Most other variables exhibit acceptable VIFs (<10 but >1), suggesting the regression model is generally stable.

Table:3.1 Two-Step Arellano-Bond Dynamic Panel-data Estimation

Sustainability Cost Dimension:1 Tax Compliance Cost				
Variable	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
L1.LTDR	0.616*** (0.000)	0.627*** (0.000)	0.757*** (0.000)	0.721*** (0.000)

Table:3.1 Two-Step Arellano-Bond Dynamic Panel-data Estimation**Sustainability Cost Dimension:1 Tax Compliance Cost**

Variable	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
D_PROF	0.020(0.712)	-0.296*** (0.000)	-0.080(0.535)	-0.240** (0.024)
D_LIQ	-0.043(0.581)	-0.016*** (0.000)	-0.044(0.227)	-0.007** (0.016)
D_GROW	0.018** (0.029)	0.050(0.177)	-0.005(0.248)	0.047(0.109)
D_BR	0.030(0.677)	-1.692*** (0.000)	0.888** (0.000)	-0.237(0.602)
D_CF	0.045(0.588)	0.257(0.001)	-0.476** (0.017)	-0.148(0.180)
D_PROF X TCC	-7.182*** (0.000)	-5.688(0.344)	-2.740(0.142)	-25.649*** (0.000)
D_LIQ X TCC	0.059*** (0.007)	-0.140** (0.011)	-0.054*** (0.000)	-0.457*** (0.000)
D_GROW X TCC	-0.727*** (0.006)	-0.302** (0.042)	1.380*** (0.000)	2.194*** (0.000)
D_BR X TCC	7.063*** (0.003)	11.580(0.103)	4.233*** (0.000)	37.938*** (0.000)
D_CF X TCC	7.653** (0.016)	5.705** (0.043)	0.605(0.827)	26.845*** (0.000)
D_SIZE	-0.014*** (0.000)	0.023*** (0.000)	0.017*** (0.006)	-0.006(0.240)
Wald (joint) test	166.522*** [0.000]	187.720*** [0.000]	242.448*** [0.000]	309.713*** [0.000]
AR(1) z	-3.763*** [0.000]	-3.903*** [0.000]	-4.184*** [0.000]	-4.482*** [0.000]
AR(2) z	-1.553 [0.120]	-1.821 [0.069]	-0.332 [0.740]	-1.469 [0.142]
Sargan test	84.972 [0.492]	47.687 [0.325]	50.0685 [0.245]	47.687 [0.325]
Hansen Test	43.673 [0.486]	48.442 [0.298]	49.1893 [0.522]	51.901 [0.193]
Instruments	55	56	55	56
Observations	715	715	715	715

Note(s): ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Source(s): Authors Own Compilation.

Table: 3.2 Two-Step Arellano-Bond Dynamic Panel-Data Estimation**Sustainability Cost Dimension:2 Logistics Cost**

Variable	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
L1.LTDR	0.660*** (0.000)	0.730*** (0.000)	0.745*** (0.000)	0.712*** (0.000)
D_PROF	0.302*** (0.000)	-0.190* (0.061)	-0.256** (0.018)	-0.565*** (0.000)
D_LIQ	-0.019*** (0.000)	-0.004*** (0.001)	-0.086(0.196)	-0.010** (0.017)
D_GROW	0.019** (0.018)	0.017(0.686)	-0.015* (0.086)	0.007** (0.043)

Table: 3.2 Two-Step Arellano-Bond Dynamic Panel-Data Estimation**Sustainability Cost Dimension:2 Logistics Cost**

Variable	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
D_BR	1.213*** (0.000)	-1.746*** (0.000)	0.586 (0.264)	0.182 (0.631)
D_CF	0.693*** (0.000)	0.372*** (0.001)	-1.106*** (0.000)	-0.234** (0.045)
D_PROF X LC	6.837*** (0.000)	-30.045*** (0.000)	-7.656*** (0.000)	7.740*** (0.000)
D_LIQ X LC	0.052*** (0.000)	0.082** (0.022)	-0.030** (0.037)	0.058 (0.229)
D_GROW X LC	0.439*** (0.000)	-0.175*** (0.000)	-0.102 (0.252)	0.005 (0.867)
D_BR X LC	-3.423 (0.422)	10.639*** (0.001)	8.351*** (0.000)	-7.387*** (0.004)
D_CF X LC	-23.600*** (0.000)	41.083*** (0.000)	15.806*** (0.000)	-9.359*** (0.000)
D_SIZE	0.038*** (0.000)	0.023*** (0.000)	0.0145** (0.015)	0.052 (0.247)
Wald (Joint) Test	242.448*** [0.000]	199.399*** [0.000]	298.595** [0.000]	268.053*** [0.000]
AR(1) z	-3.804*** [0.000]	-3.884*** [0.000]	-4.135*** [0.000]	-4.412*** [0.000]
AR(2) z	-1.868 [0.162]	-1.608 [0.108]	-0.303 [0.762]	-1.195 [0.232]
Sargan Test	46.337 [0.376]	46.419 [0.373]	47.517 [0.331]	52.467 [0.179]
Hansen Test	50.069 [0.245]	48.286 [0.309]	47.867 [0.319]	52.266 [0.184]
Instruments	55	56	55	56
Observations	715	715	715	715

Note(s): ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Source(s): Authors Own Compilation.

Table: 3.3 Two-Step Arellano-Bond Dynamic Panel-Data Estimation**Sustainability Cost Dimension:3 Digitisation Cost**

Variable	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
L1.LTDR	0.645*** (0.000)	0.638*** (0.000)	0.745*** (0.000)	0.713*** (0.000)
D_PROF	0.030 (0.679)	-0.356*** (0.000)	-0.013 (0.927)	-0.341*** (0.002)
D_LIQ	-0.001*** (0.000)	-0.002*** (0.003)	-0.046 (0.160)	-0.007** (0.021)
D_GROW	0.03 (0.624)	0.027 (0.435)	-0.011 (0.180)	0.047 (0.203)
D_BR	1.319*** (0.000)	-1.713*** (0.000)	0.656 (0.286)	-0.102 (0.813)
D_CF	0.018 (0.834)	0.332*** (0.000)	-0.748*** (0.000)	-0.030 (0.786)
D_PROF X DC	-82.829** (0.019)	-8.110*** (0.256)	-80.539** (0.012)	2.638 (0.774)
D_LIQ X DC	0.726** (0.012)	48.859** (0.026)	-0.444 (0.544)	-85.471*** (0.000)

Table: 3.3 Two-Step Arellano-Bond Dynamic Panel-Data Estimation

<i>Sustainability Cost Dimension:3 Digitisation Cost</i>				
<i>Variable</i>	Model-1		Model-2	
	(Dependent Variable-LTDR)		(Dependent Variable-STDR)	
	Before GST	After GST	Before GST	After GST
D_GROW X DC	7.706*** (0.008)	151.746** (0.041)	2.777** (0.016)	-181.353 (0.226)
D_BR X DC	72.591** (0.031)	4370.540 (0.115)	165.164*** (0.001)	12186.570*** (0.004)
D_CF X DC	44.010 (0.524)	-25353.110*** (0.000)	163.177* (0.070)	-5445.307 (0.229)
D_SIZE	-0.015*** (0.000)	0.0240*** (0.000)	0.017*** (0.000)	0.024*** (0.000)
Wald (joint) test	108.666*** [0.000]	203.536*** [0.000]	253.913*** [0.000]	277.411*** [0.000]
AR(1) z	-3.815*** [0.000]	-4.956*** [0.000]	-4.068*** [0.000]	-4.800*** [0.000]
AR(2) z	-1.643 [0.100]	-1.822** [0.068]	-0.177 [0.8596]	-1.315 [0.188]
Sargan test	48.950 [0.281]	49.023 [0.279]	49.252 [0.271]	51.988 [0.191]
Hansen Test	49.345 [0.268]	45.829 [0.251]	49.779 [0.254]	51.917 [0.210]
Instruments	55	56	55	56
Observations	715	715	715	715
<i>Note(s): ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.</i>				
<i>Source(s): Authors Own Compilation.</i>				

From table, 3.1, 3.2 and 3.3 it is observed that,

Before GST, firms' profitability generally encouraged long-term borrowing, but after GST it started discouraging it. Liquidity always reduced long-term debt, showing that firms prefer using internal funds when they have enough liquid assets. Growing firms continued to rely more on long-term debt in both periods, while business risk switched from boosting long-term borrowing before GST to reducing it after GST. Cash flow consistently supported higher long-term debt in both periods.

For short-term debt, profitability and liquidity reduced borrowing throughout. Growth, which previously reduced short-term debt, started increasing it after GST, indicating firms became more willing to use short-term funds to capture new opportunities. Business risk also turned from positive to negative after GST, meaning firms became more cautious about taking short-term debt. Cash flow consistently lowered short-term debt, as stronger cash flows reduced the need for short-term borrowing.

Furthermore, the moderation effects of sustainability cost dimensions of TCC, LC, and DC also shifted considerably:

- Tax Compliance Costs gradually reduced in post-GST, indicating that GST tax reforms helped to minimize the compliance cost burden on firms' capital structure decisions.
- In post-GST, Logistics Costs undergoes an orientation change, however the significance level of debt determinants remained same. GST enhanced logistics efficiency and cost management which significantly influences firms' reduced dependence on external financing.
- Conversely, Digitisation Costs depicts mixed effects before and after GST, implying that digital investments continue to impact capital structure, but, still remains largely unaffected by the implementation of GST however in a subjective manner.

The introduction of GST has reasonably reshaped the pattern of sustainability-related costs (viz. tax compliance, logistics, and digital transformation) that affect the linkage between key determinants of debt (like profitability, liquidity, growth, risk, and cash flow) and firms' capital structure choices. In India's consumer goods SME industry, these reforms have redefined financial strategies, as new cost structures manipulate how companies manage debt and financing decisions notably. Hence, businesses have restructure their leverage policies that well aligns with evolving regulatory and operational conditions, reflecting a more strategic and adaptive approach to financial managers in the post-GST period.

5. Concluding Remarks

During pre-GST reform, Small and medium-sized firms in India struggled with high compliance and logistics costs that often made it difficult to manage debt in a sustainable way. Many had to choose between meeting tax obligations and maintaining a stable capital structure. However, the implementation of GST has simplified and reduced compliance costs significantly, that helps these firms to strengthen their long-term financial health, even though some short-term financing issues still persisted. GST also brought major betterment in logistics efficiency, declining environmental and transportation costs. This not only encouraged greener logistics practices but also enhanced liquidity and enabled firms to handle more long-term debt responsibly. Improved logistics further created social benefits by generating employment opportunities and supporting community development. Moreover, digital investments continued to play a key role in promoting sustainable financing both before and after GST. GST itself did not change this relationship radically, however, it facilitated greater digitization,

allowing firms to cut costs, boost transparency, and better manage sustainability-related factors and associated financial risks. In due course, these improvements plausibly enabled firms to redirect savings toward productive, sustainable investments by strengthening both environmental and social dimensions of their operations.

Consequent to above findings, the study suggests that Indian consumer goods SMEs should focus on building sustainable capital structures supported by strategic cost management. By emphasizing digital transformation, optimizing logistics networks, and aligning decisions with ESG principles, these firms can achieve scalable and resilient growth. In the future, policy efforts should prioritize the regulatory simplification, furthermore, enhancing governance standards, and promoting green investments to foster sustainable development among SMEs.

References

- Allen, Franklin. 2012. "Trends in financial innovation and their welfare impact: an overview." *European Financial Management* 18 (4): 493-514.
- Almendros, Jose A. Clemente, and Francisco Sogorb Mira. 2018. "Costs of debt, tax benefits and a new measure of non-debt tax shields: examining debt conservatism in Spanish listed firms: *Revista de Contabilidad-Spanish Accounting Review* 21 (2): 162-175.
- Antoch, Jaromír, Jan Hanousek, Lajos Horváth, Marie Hušková, and Shixuan Wang. 2019. "Structural breaks in panel data: Large number of panels and short length time series." *Econometric Reviews* 38(7): 828-855.
- Arellano, Manuel, and Stephen Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The review of economic studies* 58(2): 277-297.
- Becker, Annette, Serena Fatica, and Michela Rancan. 2025. "Not only green: Sustainability and debt capital markets." *Journal of International Money and Finance* 154: 103-319.
- Baltagi, Badi Hani, 2008. *Econometric analysis of panel data*. Chichester: John Wiley & Sons, 4.
- Banerjee, Arindam, and Anupam De. 2015. "Impact of capital structure decisions on financial performance during pre-and post-recession period." *Management and Labour Studies* 40 (1-2): 176-193.
- Bruce-Twum, Ernest, and Danie Schutte. 2021. "Tax compliance cost: A review of methodologies of recent studies." *Academy of Accounting and Financial Studies Journal* 25(4): 1-10.
- Chen, An, and Tom Pohlshmidt. 2025. "Sustainability-Linked Debt, Capital Structure, and Endogenous Default." SSRN: 1-39.
- Das-Gupta, Arindam. 2004. *The economic Theory of tax compliance with special reference to tax compliance costs*. Publications Unit, National Institute of Public Finance and Policy.
- Degryse, Hans, Peter De Goeij, and Peter Kappert. 2012. "The impact of firm and industry characteristics on small firms' capital structure." *Small business economics* 38(4): 431-447
- Donaldson, Gordon. 1961. *Corporate debt capacity: A study of corporate debt policy and the determination of corporate debt capacity*. Beard Books.
- Eldomiaty, Tarek I. 2008. "Determinants of corporate capital structure: evidence from an emerging economy." *International journal of commerce and management* 17(1/2): 25-43.
- Hsiao, J., C. Hsu, and K. Hsu. 2009. "An Empirical Study on Capital Structure and Financing Decision: Evidences from East Asian Tigers." *The Business Review, Cambridge* 13(1): 248-253.
- Jensen, Michael C., and William H. Meckling. 2019. "Theory of the firm: Managerial behavior, agency costs and ownership structure." In *Corporate governance* Gower: 77-132.
- Jung, Juan, and Gonzalo Gómez-Bengoechea. 2022. "A literature review on firm digitalization: drivers and impacts." *Estudios sobre la Economía Española* 20.
- Kusumawardhani, Fieryanti Kamaril, Dwi Ratmono, Septa Tri Wibowo, Darsono Darsono, Singgih Widyatmoko, and Nur Rokhman. 2024. "The impact of digitalization in accounting systems on information quality, cost reduction and decision making: Evidence from SMEs." *International Journal of Data and Network Science* 8 (2): 1111-1116.

- López-Gracia, José, and Francisco Sogorb-Mira. 2008. "Testing trade-off and pecking order theories financing SMEs." *Small Business Economics* 31(2): 117-136.
- Mateev, Miroslav, Panikkos Poutziouris, and Konstantin Ivanov. 2013. "On the determinants of SME capital structure in Central and Eastern Europe: A dynamic panel analysis." *Research in international business and finance* 27(1): 28-51.
- Mitra, Sayak. 2022. "Impact of Capital Structure Determinants in Financing Decision: A Study Based on Listed Small and Medium Enterprises in India", M.Phil. diss., University of Kalyani, Kalyani.
- Mitra, Sayak, and Pradip Kumar Samanta. 2022. "Leverage tax benefit, non-debt tax shield, default risk and external financing policy of listed small and medium-sized transportation companies: a panel data approach." *SKBU Business Review* 2 (1): 38-70. Mitra, Sayak, Rupa Mondal, and Saurav Mukherjee. 2023. "Select Firm Specific Determinates and Debt Procurement Policy of Small and Medium Sized Indian Health Sectors Firms: A Generalised Methods of Moment Approach." *Management Journal for Advanced Research* 3(1): 26-34.
- Mushtaq, Rizwan. 2021. "Augmented dickey fuller test", *Working Paper*, Université Paris I Panthéon-Sorbonne, PNS. August, 17 August.
- Mwika, Dickson, Alick Banda, Christopher Chembe, and Douglas Kunda. 2018. "The impact of globalization on SMEs in emerging economies: A case study of Zambia." *International Journal of Business and Social Science* 9 (3): 59-68.
- Pohit, Sanjib, Devendra B. Gupta, Devender Pratap, and Sameer Malik. 2019. "Survey of literature on measuring logistics cost: A developing country's perspective." *Journal of Asian Economic Integration* 1(2): 260-282.
- Rahman, Asma Rina Abdul, Noor Ayuernie Ibrahim, and Suria Abu Basar. 2021. "The Effect of Capital Structure on the Performance of Malaysian PLCs During a Transition From SST To GST." 3(6): 69-81.
- Rao, Purnima, Satish Kumar, and Vinodh Madhavan. 2019. "A study on factors driving the capital structure decisions of small and medium enterprises (SMEs) in India." *IIMB Management Review* 31(1): 37-50.
- Roodman, David. 2009. "A note on the theme of too many instruments." *Oxford Bulletin of Economics and statistics* 71(1): 135-158.
- Ruri, Joseph Kinyua, and Job Omagwa. 2018. "Capital structure and financial performance of small and medium enterprises in Embu County, Kenya." *Journal of Business and Management* 20(5): 1-10.
- Sahoo, A., and A. Swain. 2017. "Implementation and its impact of GST on industrial sectors: An analytical study." *International Journal of Innovative Research in Science, Engineering and Technology* 6(7): 15173-15180.
- Savlovski, Ludovica Ioana, and Nicoleta Raluca Robu. 2011. "The role of SMEs in modern economy." *Economia, Seria Management* 14(1): 277-281. Mac an Bhaird, Ciarán, and Brian Lucey. 2010. "Determinants of capital structure in Irish SMEs." *Small business economics* 35(3): 357-375.
- Sinha, Sandip. 2017. "Determinants of Capital Structure: An Empirical Study of Selected Indian Manufacturing Companies", PhD Thesis, University of Kalyani, Kalyani.
- Sogorb-Mira, Francisco. 2005. "How SME uniqueness affects capital structure: Evidence from a 1994–1998 Spanish data panel." *Small business economics* 25(5): 447-457.
- Vishnuhadevi, S. and Bindu, D. Hima. 2022. "Compliance Costs of GST for Small Business Enterprises in Tamil Nadu." *Working Paper*: 1-51.
- Costea, Andrei. 2021. "KPI of the Day – Logistics: % Distribution cost" *Performance Magazine, the KPI Institute*. May, 31. Clear tax. 2025. "Impact of GST on Logistics Industry". Last updated on January, 21. Press Information Bureau, Govt. of India. 2025. "GST Reforms Power India's Green Transition". Last updated on September, 21 at 10:05 (GMT).



Emerging Technology in Financial Crime Compliance

Sriram Narasimhan^a

^a*LTIMindtree*

Abstract

Banks and Financial services are evolving rapidly with increased adoption of technology. With this evolution comes increase in financial crime. The methods used for financial crime have become more sophisticated and complex. The rule based applications used to combat financial crime are inadequate and banks are looking at using emerging technologies like machine learning to combat financial crime.

The article addresses the use cases of financial crime compliance where emerging technology and machine learning can be used from the perspective of operational efficiency, risk reduction and enhanced compliance. We are also seeing increased interest in this space from regulators and government entities. Many product companies have embraced the use of emerging tech and artificial intelligence in financial crime compliance and the article also addresses how algorithms can learn from historical data, identify patterns and make predictions to assist financial crime compliance.

Keywords: Financial Crime, Compliance, Artificial Intelligence, Machine learning, Fraud detection

1. Introduction

At the outset, the banking and financial services sector is faced with an avalanche of advanced financial crime methods and has led to banks thinking about adoption of emerging tech, AI and Machine Learning in combatting financial crime. While the technology product firms have embraced these innovations to a large extent banks are viewing this with cautious optimism as given the stringent regulations and the substantial fines by the regulator would mean necessitate getting the implementation of emerging tech right in this space.

However, As per the World Economic Forum financial services firms have spent 35 billion on AI till 2023 and it is going to rapidly increase with advent of Generative and Agentic AI.

In India, the RBI Free AI framework guidelines and SEBI role in utilizing AI for fraud detection AI are opening the doors for innovation in this space.

The FATF (Financial Action Task Force), the volume of fraudulent transactions is estimated to be 2% to 5% of the total GDP.

The combination of financial crime being more sophisticated and the regulator signalling the use of emerging technology, AI and Machine Learning has led to increased adoption in this space for specific use-cases like fraud detection, anti-money laundering, KYC and Sanctions Screening.

Furthermore, there are limitations to existing rule based applications and technology and are increasingly ineffective in combatting financial crime. Most of these techniques are reactive and not real-time and there are numerous false positives which increases the workload of the bank operations team.

2. Financial Crime, Anti Money Laundering and Fraud Detection

Financial crime compliance encompasses a series of policies and procedures that institutions like banks, investment firms, asset managers, and insurance companies must implement to detect and prevent financial criminal activities. The regulatory framework outlines various obligations aimed at ensuring responsible conduct. Key requirements include conducting risk assessments on potential threats, performing customer due diligence regarding identities and

business relationships, implementing enhanced due diligence for high-risk clients, continuously monitoring customer interactions and transactions, reporting suspicious activities, and maintaining comprehensive records related to customer due diligence.

Fraud detection refers to recognizing fraudulent actions or attempts related to money laundering or theft.

Regulatory adherence concerning financial crime risk management remains essential for banking institutions. Many organizations still find managing financial crime risks complex and inefficient.

3. Advancement in AI and ML

Turing's predictions in 1950 laid a foundational understanding for AI and the 1990 and 2000 saw the development of neural networks in financial services. The pervasiveness of data and increase in computing power have seen the advancement of AI and ML in today's context.

Considerable investments have been made by nations to harness the benefits of AI. Advances in Computer Vision, ML and NLP have enabled AI to perform complex tasks. The field of Generative AI has seen great progress with the development of Large Language Models (LLMs) Quantum AI using the properties of Qubits might surpass the limitations of classical AI by solving problems which could not be solved due to computational constraint.

AI that proactively makes decisions on its own will revolutionize the impact it has on corporations. Robotic Process Automation coupled with ML have given rise to Agentic AI and Agentic AI has systems composed of specialized agents that operate independently, each handling specific tasks.

4. Use Cases of AI in Financial Crime and AML – The role of AI in FCC

There are various areas in the Financial Crime value chain which are seeing increased adoption of AI and emerging technology including Fraud Detection and Transaction Monitoring, Enhanced Due Diligence and KYC, Suspicious Activity Reporting, Sanctions Screening and PEP Screening.

Fraud Detection and Transaction Monitoring: Agentic AI systems can detect fraudulent transactions and anomalies at real-time. Supervised learning and classification algorithms train on fraudulent data to classify transactions.

EDD and KYC: Banks use Identity verification and risk scoring for KYC using Computer Vision and Facial recognition. Enhanced Due Diligence is a set of procedures to assess customers based on their risk profiles. Knowledge graphs and Graph Neural Networks for mapping complex relationships, risk profiling are used in EDD.

Generation of SARs: Banks and financial services firms produce SARs to alert regulators on potential suspicious transactions. GenAI can be leveraged to generate these reports and NLP can be used to process the description on these reports to route it to law enforcement agencies.

Sanctions Screening and PEP: AI Agents uncover hidden relationships between PEP and Relatives and Close Associates and for entities which are Sanctioned through multilingual and social analysis and processing with Named Entity Recognition and social media analysis with graph classification.

5. Regulators Adoption of AI in Financial Crime Compliance over the last few years

Reserve Bank of India

RBI has developed a Digital Payments Intelligence Platform which is Centralized fraud intel and real-time risk scoring. It is a national intelligence-sharing and fraud account repository platform for all digital transactions in India. It has enabled Fraud detection across the payment ecosystem and the Collaborative AI-powered fraud detection that identifies suspicious patterns across banks, payment providers, and digital wallets in real-time or in T+1 batches. RBI also launched an Artificial Intelligence (AI) and Machine Learning (ML) based model, namely MuleHunter, to prevent and mitigate digital fraud by using mule accounts.

Additionally, RBI FREE-AI framework - the Reserve Bank of India's guidance for how AI should be responsibly adopted, governed, and deployed in India's financial sector.

Financial Action Task Force Report in July 2021 – Opportunities and Challenges of New Technologies for AML/CFT

Digital Identity Solutions that can enable non-face-to-face customer identification/verification/authentication and updating of information

AI/ML Technology-based Solutions that can be applied to big data can strengthen ongoing monitoring and reporting of suspicious transactions

Natural Language Processing that can support more accurate, flexible, and timely analysis of customer information

6. Emerging Technology in the Financial Crime and Compliance space

1. Classical AI and Machine Learning Models

Supervised and unsupervised learning models detect patterns that rules-based systems miss, improving the precision of alerts in fraudulent transaction detection.

Random Forest/XGBoost – This algorithm is generally used for classification tasks which are trained on historical data labelled as ‘fraudulent’ and ‘non-fraudulent’.

Support Vector Machine – This algorithm flags anomalies by creating a ‘hyperplane’ – boundary around normal data points and flags the outliers as anomalies to identify ‘fraudulent’ transactions.

K-Means clustering groups similar transactions or behaviours to detect anomalies.

Product companies typically use a champion challenger model where one new model challenger model replaces the champion model if the performance of the model improves with additional data or new features.

2. Quantum Computing

For highly imbalanced data sets, quantum computing is used to more accurately identify fraudulent transactions. Classical machine learning based predictions and classifications are good but has limitations when it comes to highly imbalanced data. In such scenario they often struggle to have better Precision and Accuracy and could lead to False Positives and False Negatives. We use Quantum Support Vector Machine algorithm for the Transaction monitoring / Fraud Detection use cases that is based on the classification of labeled data. Quantum Machine Learning (QML) leverages quantum mechanical

phenomena like Superposition and Entanglement, which helps QML models uncover the hidden patterns.

3. Generative AI

Generative Adversarial Networks is used to create synthetic data to improve the accuracy of the predictions as well. Also Generative AI can be used to automatically generate Suspicious Activity Report and NLP is used to process the SAR reports and route it downstream entities as well..

4. Fuzzy Logic

AI-driven fuzzy matching identifies near-match names against sanction lists consolidating identities derived from diverse sources seamlessly functioning together

5. Knowledge Graphs and Ontology

To combat modern fraud, banks and financial institutions must adopt intelligent, interconnected, and autonomous systems that leverage AI for fraud detection. This entails:

Ontology: It defines the semantic structure of financial entities such as customers, accounts, transactions, vendors, as well as their relationships. It enables systems to understand meaning, not just data.

Knowledge Graphs: These map real-time relationships between entities. For example, a graph can show how a customer is linked to multiple accounts, vendors, and geographies. It helps detect unusual patterns, such as a customer suddenly transacting with high-risk countries.

6. Computer Vision

For KYC, facial recognition can be used to detect customer's identity to prevent fraud during onboarding.

7. Agentic AI

Agentic AI is very useful in transaction monitoring and fraud detection in real-time. Agentic AI can autonomously plan and execute a sequence of actions to achieve a specific goal. A key strength of agentic AI is its ability to break down complex problems and adapt its actions based on context and feedback. This is achieved by orchestrating multiple specialized AI "agents" that work together seamlessly, such as a "PEP agent" or "Monitoring agent" or "Payment initiation agent".

7. Quantitative Analysis

An analysis of how to Build better classification, prediction approach for fraud detection and risk assessment by leveraging Quantum Machine Learning

Problem Statement:

Overcome the limitations of Classical machine learning algorithm in classification of Imbalanced Data:

Classical machine learning based predictions and classifications are good but has limitations when It comes to highly imbalanced data. In such scenario they often struggle to have better Precision and Accuracy and could lead to False Positives and False Negatives. We have used Quantum Support Vector Machine algorithm for the Transaction monitoring / Fraud Detection use cases that is based on the classification of labeled data.

Infrastructure: We have executed our Program on IBM Quantum system

Quantum Machine Learning (QML) leverages quantum mechanical phenomena like Superposition and Entanglement, which helps QML models uncover the hidden patterns and correlations between data points of complex, inadequate, and imbalanced data sets.

Solution : We used data-set preprocessing to improve the quality of data for fraud detection.

- To model the data-set we used the Quantum Support Vector Machine (QSVM)
- For encoding classical data into quantum bits ZZ- FeatureMap is used
- Simultaneous Perturbation Stochastic Approximation (SPSA) optimization was used to optimize the hyperparameters for the kernels to achieve highest accuracy.

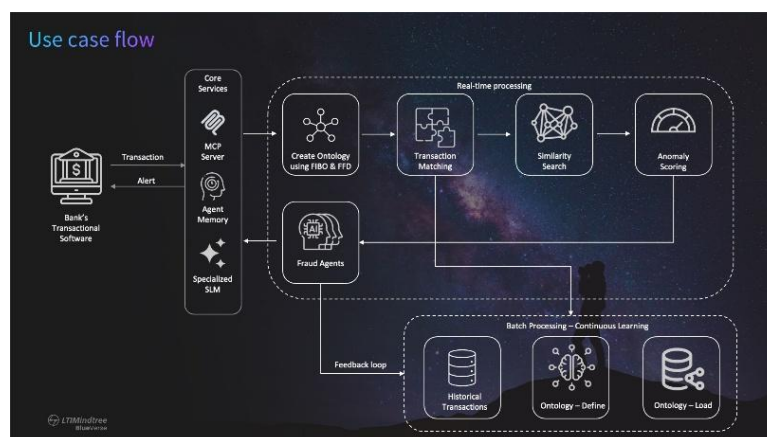
- Quantum kernel is used to compute the kernel matrix which helps in constructing the hyperplane

Higher Prediction Accuracy: Quantum SVM experimentation generated promising results on **IBM Quantum system**, such as improved prediction accuracy in the case of transaction fraud detection benchmarked against Classical SVM.

Classical SVM	Precision	Recall	F1-score	Support
0	0.97	0.997	0.98	479
1	0.86	0.30	0.44	20
Macro avg	0.91	0.65	0.71	499

Quantum SVM	Precision	Recall	F1-score	Support
0	0.98	1.00	0.99	479
1	1.00	0.60	0.75	20
Macro avg	0.99	0.80	0.87	499

An analysis of how to build a next gen fraud management approach using Agentic AI - Agentic AI orchestrates real-time multi-agent detection, using contextual cues, memory, and dynamic reasoning to flag anomalous behaviour as it occurs. It also embeds human-in-the-loop feedback for continuous improvement.



8. Challenges and Risks of AI in Financial Crime Compliance

- **Explainability and Model transparency:** A challenge in this area is that it is highly regulated so explainability and transparency of the models is an imperative. Models using Neural Networks find it a challenge for it to be explainable.
- **Data privacy:** Data privacy poses few distinct challenges. The tenets of data minimization and purpose limitation inhibit the exploratory data analysis from collecting the whole dataset needed to train the model. So we have to implement a robust data governance framework and use a robust privacy enhancing mechanism.
- **Regulatory and compliance challenges:** Supervisors require assurance that AI does not weaken compliance standards.
- **Imbalanced datasets:** The number of fraudulent transactions which occurs to the total number of transactions is very minimal. 1 in 100 or 1 in 1000. The practical strategy is to generate synthetic data to be generated to increase accuracy using Generative Adversarial Networks or to use Quantum Machine Learning in addition to classical flow for better results.
- **Algorithmic Bias-** Algorithmic bias and hallucinations are reduced by having humans in the loop for decision making. This also balances automation with customer trust. AI will aid and abet humans in decision making not replace them.
- **Interoperability between IT Legacy Systems and AI –** One of the technical challenges is interoperability with IT systems and AI and use of tools like MCP and A2A and building interfaces with Legacy systems will help address this challenge.

9. Conclusion

Of all the major technology developments in the last 25 years – Moore’s Law and the personal computer, internet, mobile phones and currently it is AI. AI is neither a saviour which will solve everything nor replace humans.

Financial Crime, Anti-Money Laundering and Fraud Detection is one area where emerging technologies like AI and Machine Learning have a big role to play in improving operational efficiency, risk reduction and cost savings.

There is tremendous potential for use of AI in financial crime in making tasks and life easier which aid and abet humans in their day to day jobs. We must to a large extent have a human in the loop for decision making.

With the advent of increased sophistication in financial crime , fraud investigators can uncover fraud long after the transaction takes place as well as in real-time in some cases.

Real success in AI stems for solving problems in this space requires all entities government , organizations , leaders and society to focus the use of emerging technologies in solving challenges which they are facing.

References

Ahmad Naser Eddin 1, Jacopo Bono 1 et al - Anti-Money Laundering Alert Optimization Using Machine Learning with Graphs

New York City Bar - Artificial Intelligence and Machine Learning in Financial Services – Opportunities and challenges in AML and combatting the financing of terrorism

Faheem Ashraf , Alejandro Schaffer - Combating Financial Crime: AI and Machine Learning in Anomaly Detection and Risk Management

[Digital Payments Intelligence Platform — RBIH](#) – Centralized fraud intel and real-time risk scoring

[MuleHunter.ai — RBIH](#) - Detect and flag mule accounts in near real-time

[Opportunities and Challenges of New Technologies for AML/CFT](#) – FATF



Does Entrepreneurship Drive Economic Growth? Insights from India

Sagartirtha Chakraborty^a, Suresh Kumar Nath^b

^{a,b} *Department of Economics, Cotton University, Assam*

Abstract

Entrepreneurship is the process of ‘creative destruction’ and it is viewed as one of the main supporting blocks of economic growth. Considering a period of 24 years from 2001 to 2024, we assess the relationship between economic growth and entrepreneurship in India. Findings from multivariate regression analysis highlight that entrepreneurship is a significant driver of India’s economic growth. However, challenges such as continued limitations on ease of doing business, skewed distribution of capital, lack of product demand, and skill deficits still hinder the nation’s entrepreneurial landscape. We finally discuss how our entrepreneurial ecosystem requires adequate government funding in R&D, patent application approvals, incubation networks in tier-II and tier-III cities, and the integration of targeted skill development programmes to continue to drive the nation’s sustained economic growth.

Keywords: Entrepreneurship, Economic growth, GDP, Innovation, Startup, Investment, India.

JEL Classification: L26, O47, O11.

1. Introduction

Entrepreneurship is one of the main pillars of economic growth. Classical economists such as Adam Smith associated entrepreneurs with capitalists, while J.B. Say correlated them with business organisers. However, it was Joseph Schumpeter who termed entrepreneurs as the driving force of ‘creative destruction’ through which they displace the out-of-date ideas, technologies, and institutions with new ones to enable long-run growth of the economy (Schumpeter 2021). In present times, entrepreneurship is defined as the process through which people identify, evaluate, and take advantage of opportunities to create new products, services, or ventures (Shane and Venkataraman 2000). In developed countries, productivity-enhancing technological change, competitiveness, and the emergence of high-growth ‘gazelle’ companies that facilitate output have been associated with entrepreneurship-led innovation (WEF 2023; Neumeyer et al. 2025). Similarly, entrepreneurship in East Asian economies such as South Korea and Taiwan supplements the state-driven industrial policies by rapidly broadening technological upgrading and export diversification (Perkins and Tang 2017). Research indicates that even in emerging economies, where entrepreneurship is largely compelled by necessity, an increase in innovation-based ventures positively impacts labour productivity, formalisation of firms, and economic resilience during structural transitions (Hamdan et al. 2021).

In the context of India, Subrahmanya (2021) mentioned how the country’s entrepreneurial ecosystem matured significantly between 2006 and 2015 due to the rise of Flipkart, Snapdeal, Ola, PayTM, and other internet-based startups, especially in cities like Bangalore and Hyderabad. In this regard, factors such as rising smartphone penetration, influx of global venture capital, and development of entrepreneurial hubs in cities like Bengaluru have been the most influential ones (Jha 2018). The Indian entrepreneurial ecosystem has been further institutionalised by the introduction of the ‘Startup India’ initiative in 2016, which has been providing assistance in terms of capital access, simplified patent processes, tax holidays, and easing procedures to start a business. As of 2024, over 1.67 million startup-based entrepreneurs are in operation in various states of India with a valuation of 349.67 billion (Ministry of Commerce and Industry 2025). The presence of such a broad entrepreneurial ecosystem, if coupled with robust institutions, financial depth, and increased innovation capacity, can play a vital role in boosting the GDP and productivity of the country.

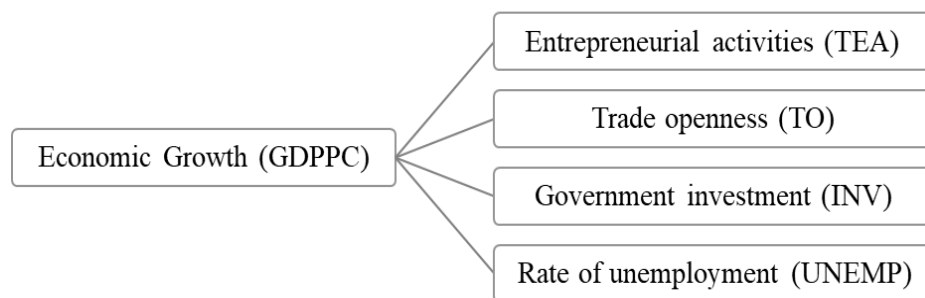
However, despite promising trends, the macro-level linkage of entrepreneurial activity and economic growth is under-explored in India. The existing literature has primarily concentrated

on micro-level predictors of entrepreneurship either in startups or MSMEs. This study tries to address the gap with respect to how the growth of entrepreneurship in the presence of different macroeconomic factors, like trade openness, government investment, and labour market conditions, influences India's economic growth. In addition to that, it further explores the challenges faced by Indian entrepreneurs that hinder its growth.

2. Research Methodology

We use secondary data to carry out the study, which are collected from the World Bank's World Development Indicators and Global Entrepreneurship Monitor (GEM) reports. We run time-series modelling to explore the relationship between economic growth and entrepreneurship in India between 2001 and 2024.

Figure 1: Conceptual framework of the study



Source: Authors' construction

As a proxy of economic growth, the growth rate of GDP per-capita (GDPPC) is considered, since it captures the health of an economy by accounting for standard of living. As demonstrated by [Li et al. \(2023\)](#), a better standard of living provides a favourable business ecosystem that supports entrepreneurship by enhancing human capital through innovation, infrastructural development, and providing swift access to financial resources. On the other hand, the total early-stage entrepreneurial activity (TEA) is our prime independent variable. It is used as a proxy to measure entrepreneurship growth. TEA considers the percentage of the population within the age bracket ranging between 18 and 64 years of age, who either intend to start a new entrepreneurial activity or are already the owners of an enterprise ([GEM 2025](#)). We have further included certain macroeconomic variables in the model to be able to explain its infrastructural heterogeneity. It includes trade openness (TO) as a proportion of trade to GDP, a factor that is known to drive economic growth, which facilitates innovation, competition, and productivity by integrating domestic economies with international markets

(Seti, Mazwane, and Christian 2025). Again, the ratio of total government investment to GDP represents another variable (INV). Government investment contributes positively to the economic growth of developing countries, as it plays a vital role in building infrastructure of these economies, including roads and utilities, which is essential for minimising the cost of transactions and enhancing efficiency (Jalles, Park, and Qureshi 2024). The final macroeconomic factor is the level of unemployment (UNEMP), which refers to the share of the labour force who does not have work but is available for and willing to work. According to the World Bank (2025), rising unemployment has an adverse effect on a country's economic growth.

It should be noted that the dependent variable GDPPC is measured both in its raw form and in its natural logarithm to account for potential non-linearities and to ensure robustness in the regression outcomes. The log-log model is not used in the study, since diagnostic tests reveal the model to have the least explanatory power. Therefore, the following linear and semi-log regression models are considered for our analysis:

$$\textbf{Linear (I):} \quad GDPPC_t = \alpha_0 + \alpha_1(TEA)_t + \alpha_2(TO)_t + \alpha_3(INV)_t + \alpha_4(UNEMP)_t + \alpha_5(GDPPC)_{t-1} + u_t$$

$$\textbf{Log-lin (II):} \quad \log-(GDPPC)_t = \beta_0 + \beta_1(TEA)_t + \beta_2(TO)_t + \beta_3(INV)_t + \beta_4(UNEMP)_t + \beta_5(GDPPC)_{t-1} + u_t$$

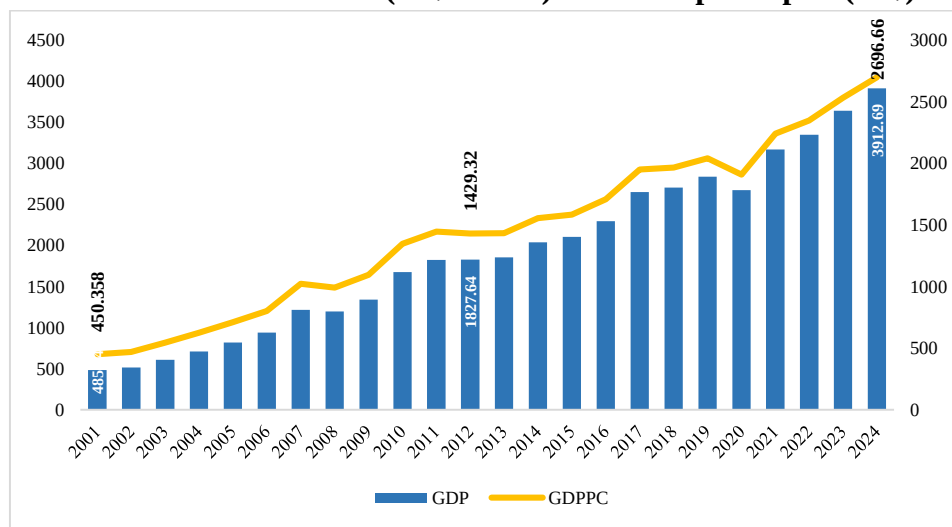
$$\textbf{Lin-log (III):} \quad GDPPC_t = \gamma_0 + \gamma_1 \log(TEA)_t + \gamma_2 \log(TO)_t + \gamma_3 \log(INV)_t + \gamma_4 \log(UNEMP)_t + \gamma_5(GDPPC)_{t-1} + u_t$$

The stationarity of the data series is verified using the Augmented Dickey-Fuller (ADF) test to avoid spurious regressions. Reliability and validity of the regression estimates are estimated through different diagnostic tests. The White's test is undertaken to assess heteroskedasticity, where a non-significant test outcome (p-value > 0.05) indicates that the model's standard errors are reliable. Furthermore, the existence of multicollinearity is tested using the variance inflation factor (VIF), where VIF staying close to zero confirms the absence of it and exceeding 10 confirms its presence. Again, the presence of autocorrelation is detected by using the Durbin-Watson test, where the d-statistic value ranging from 1.5 to 2.5 denotes the absence of it.

3. Results and Discussion

Figure-2 depicts the growth trend of India's GDP and GDP per-capita during 2001-2024. India has witnessed remarkable economic growth over the past two decades, with its GDP registering a compound annual growth rate (CAGR) of 9.08 percent from \$485.44 billion to \$3912.69 billion during the period 2001 to 2024. Correspondingly, GDP per-capita has also experienced a CAGR of 7.74 percent during the same timeframe, reflecting an improvement in the standard of living across India's demographic landscape.

Figure 2: Growth trend of GDP (in \$ billion) and GDP per-capita (in \$) in India



Source: Authors' compilation from World Bank's World Development Indicators

This sustained momentum of India's economic growth indicators has led the country to emerge as the world's fourth-largest economy in terms of total GDP, having overtaken Japan in 2025 with a nominal GDP exceeding \$4000 billion. A combination of various factors has led to this structural change. Among them, the developing entrepreneurial ecosystem with the vision of 'Atmanirbhar Bharat' is assumed to be one of the drivers of innovation-based entrepreneurial growth in the country (Kumar, Kataria, and Patiyal 2025).

Table 1: ADF test results

Variables	Test statistic	Integration order
GDPPC	-4.549***	I(0)
TEA	-4.704***	I(0)
TO	-4.105***	I(1)
INV	-3.912***	I(0)
UNEMP	-5.715***	I(0)

Source: Authors' estimation

*Note: *** indicates level of significance at 1 percent*

The ADF test results, presented in Table-1 reveal that all the variables except TO are stationary at level I(0), indicating no unit roots. However, TO denotes the presence of a unit root, which is made stationary by taking the first difference [I(1)], so that we can use OLS in estimating both linear and log-linear models.

Table 2: Results of Multivariate Regression Analysis

Variables	Coefficients		
	Model I	Model II	Model III
TEA _t	0.618**	0.057**	5.047*
TO _t	0.098	0.038	2.238
INV _t	0.457**	0.128***	14.463*
UNEMP _t	-1.095*	-0.054*	-5.259
GDPPC _{t-1}	0.001	0.013	1.474
Model Summary			
R ²	0.783	0.695	0.540
Adj-R ²	0.723	0.610	0.412
Mean VIF	1.290	1.240	1.890
White Test	0.345	0.365	0.371
DW Test	1.728	1.681	1.522

Source: Authors' estimation

*Note: ***, **, and * indicate level of significance at 1, 5, and 10 percent respectively*

Table-2 shows that the variable TEA is positive and statistically significant in all three specifications of models. This is in line with [Ordenana et al. \(2024\)](#), who have established a positive correlation between entrepreneurship and economic growth. The reason is that countries with greater entrepreneurship growth tend to enjoy enhanced market dynamism and diversification, which assists in mediating smooth cyclical shocks to spur future income growth ([Almodóvar-González, Fernández-Portillo, and Díaz-Casero 2020](#)). The endogenous growth

theory further contends how economic growth in the long term requires the development of human knowledge and human capital, where entrepreneurs play a key role (Osipian 2023). By blending new organisational structures with existing technological potentials through effective labour mobility, spreading of knowledge, and competitive pressure, they generate positive externalities, which enhance productivity (Audretsch, Belitski, and Fiedler 2025).

Among other macroeconomic factors, ‘INV’ has a significant positive relationship with economic growth across all model forms. This finding is supported by Foster, Vagliasindi, and Gorgulu (2022), who highlighted the advantageous purpose of government spending, especially in the fields of infrastructure, online connectivity, and human capital that boosts productivity and economic growth in emerging economies. Furthermore, public investment benefits technology and innovation, as a result of which governments across Asian countries are currently subsidising technology-based industries with grants and subsidies to achieve sustainable economic growth (Asian Development Bank 2018).

Again, ‘UNEMP’ has continuously displayed negative coefficients in all the models, with two models further showing its statistical significance. In theory, Okun’s law suggests that economic growth and the unemployment rate are negatively related to each other. The reason is that high unemployment reduces productivity, impairs entrepreneurial activities, affects aggregate demand, and thereby negatively impacts economic growth (Porrás-Arena and Martín-Román 2023). Moreover, rising unemployment in developing countries like India is also a sign of informality and structural rigidity, which are closely linked to slower GDPPC (Basole 2022). Finally, ‘TO’ and ‘lagged GDPPC’, although they have shown theoretically consistent signs, yet they lack statistical significance in any specification.

4. Challenges and Policy Interventions

Even though the growth of entrepreneurship has a significant impact on bolstering India’s economy, the channel through which entrepreneurs operate in the country remains constrained by various challenges. For instance, India is ranked 77th in the ‘ease of doing business’ index by the World Bank, which indicates systemic inefficiencies, opaque bureaucratic processes, and a barrier to new entrant enterprises (Korreck 2023). This can be understood through the fact that backlogs in the entrepreneurial patent applications in India have decreased 36 percent in terms of number of applications and 15 percent in terms of patent granting in 2024 as compared to 2020 (Chakraborty 2025). Moreover, capital investment still remains heavily

concentrated in cities like Bengaluru, Delhi, and Mumbai. It is only in recent times that entrepreneurs from Tier-II and Tier-III cities like Jaipur, Surat, Chandigarh, Bhopal etc., are attracting funds from capital investors, with 64 percent of those investments being made to the IT and fintech sector entrepreneurs ([Financial Express 2024](#)). Moreover, most entrepreneurs in India are encountering a lack of product demand, especially in the age of artificial intelligence (AI) and the internet of things (IoT), because of the lack of credibility. When AI is projected to add over \$15.7 trillion to the global economy by replacing conventional business models and establishing new entrepreneurial priorities, skill deficiency introduces another bottleneck in innovation, deterring economic growth ([The Hindu 2025](#)).

The magnitude of these challenges suggests that entrepreneurship alone cannot lift economic growth unless it is supported by a self-consistent ecosystem that creates ease of operation, lowers institutional uncertainty, and enhances the quality of human capital entering the entrepreneurial pipeline. Hence, the scheme of ‘Startup India: The Way Ahead’ has been introduced by the government of India to boost the ease of doing business by consolidating the capacities of the stakeholders so that the further ambition of having a digitally empowered and self-sustaining India can be achieved. Complementing this, over 55 regulatory reforms have been undertaken since 2016 to make compliance simpler and enable self-certification of the entrepreneurs. Moreover, the ‘Startups Intellectual Property Protection’ scheme offers fast-tracked and subsidised IP services to bolster innovation, while the ‘Bharat Startup Knowledge Access Registry’ (BHASKAR) scheme streamlines entrepreneurial activities by making coordination of entrepreneurs with investors, service providers, and government bodies ([Ministry of Commerce and Industry 2025](#)). Moreover, the ‘Mentorship, Advisory, Assistance, Resilience, and Growth’ (MAARG) programme aims at democratising the high-quality mentorship in various parts of India, so that they would become a global centre of skill development and entrepreneurial excellence ([Ministry of Skill Development and Entrepreneurship 2024](#)).

5. Conclusion

To sum up, the prime empirical finding of the study shows how entrepreneurship is positively associated with India’s economic growth. However, the challenges in this regard require a strategic and multi-dimensional policy response. Strengthening the entrepreneurial ecosystem needs a boost in R&D funding, expansion of incubation networks into Tier-II and Tier-III

cities, and establishing strong collaboration between the university and industry, in order for innovation-enhancing productivity of the entrepreneurs, as opposed to imitative ones, to get a push. Again, reforms that reduce procedural delays, enhance contract enforcement, increase patent filings, and improve the reliability of public infrastructure would further lower transaction costs and foster a stable ecosystem for economic growth. In this regard, India can learn lessons from South Korea's use of public procurement to support its early-stage entrepreneurs. This could offer a solution to India's recurring challenge of insufficient product demand, especially in sectors where market entry barriers are high. In this regard, expanding the 'One District One Product' framework could also be a way forward. Finally, the quality and sustainability of the entrepreneurial supply can be improved by using select skill-development programmes that combine entrepreneurship education with digital and managerial skills. To sum up, these measures can allow the Indian entrepreneurship landscape to evolve from a loosely-knit individual initiative into a systematic movement that can sustain high and inclusive economic growth.

References

- Almodóvar-González, Manuel, Antonio Fernández-Portillo, and Juan Carlos Díaz-Casero. 2020. "Entrepreneurial Activity and Economic Growth. A Multi-country Analysis." *European Research on Management and Business Economics* 26 (1): 9–17.
- Audretsch, David, Maksim Belitski, and Antje Fiedler. 2025. "The Knowledge Spillover Theory of Entrepreneurship and Innovation: Taking Stock and New Directions." *The Journal of Technology Transfer*.
- Asian Development Bank. 2018. *Asian Development Outlook (ADO) 2018: How Technology Affects Jobs: ADO*. Asian Development Bank.
- Basole, Amit. 2022. "Structural Transformation and Employment Generation in India: Past Performance and the Way Forward." *Indian Journal of Labour Economics* 65 (2): 295–320.
- Chakraborty, Sagartirtha. 2025. "Startups in the Global South Struggle for International Recognition - LSE Business Review." *LSE Business Review*. Accessed November 21, 2025.
- Financial Express. 2024. "44% of investors actively funding startup growth in Tier II, III cities: Survey." *Financial Express*. Accessed April 28, 2025.
- Global Entrepreneurship Monitor (GEM). 2025. "Global Entrepreneurship Monitor 2024/2025 Global Report." *GEM Global Entrepreneurship Monitor*. Global Entrepreneurship Research Association.
- Hamdan, Allam, Hasan Ghura, Bahaeddin Alareeni, and Reem Khamis Hamdan. 2021. "Entrepreneurship Growth in Emerging Economies: New Insights and Approaches." *Journal of Sustainable Finance & Investment* 12 (1): 1–12.
- Jalles, João Tovar, Donghyun Park, and Irfan Qureshi. 2024. "Public and Private Investment as Catalysts for Growth: An Analysis of Emerging Markets and Developing Economies with a Focus on Asia." *Journal of International Money and Finance* 148.
- Jha, Srivardhini K. 2018. "Entrepreneurial Ecosystem in India: Taking Stock and Looking Ahead." *IIMB Management Review* 30 (2): 179–88.
- Kumar, Kataria, and Patiyal. 2025. "India Becoming an Economic Powerhouse." *Press Information Bureau*. 2025. Accessed November 19, 2025.
- Li, Jiaxin, Yunzhou Du, Ning Sun, and Zhimin Xie. 2023. "Ecosystems of Doing Business and Living Standards: A Configurational Analysis Based on Chinese Cities." *Chinese Management Studies* 18 (5):

- 1302–23. Ministry of Commerce & Industry. 2025. “Nine years of Startup India.” Press Information Bureau. Accessed April 28, 2025.
- Ministry of Skill Development and Entrepreneurship. 2024. “Government initiatives to promote startups across the country.” Press Information Bureau. Accessed April 28, 2025.
- Neumeyer, Xaver, Susana C. Santos, Eric Liguori, Steven T. Walsh, and Raj V. Mahto. 2025. “The Ever-evolving Relationship Between Technology, Innovation, and Entrepreneurship: Current State and Future Research Needs.” *Technological Forecasting and Social Change* 215.
- Ordeñana, Xavier, Paúl Vera-Gilces, Jack Zambrano-Vera, and Alfredo Jiménez. 2024. “The Effect of High-growth and Innovative Entrepreneurship on Economic Growth.” *Journal of Business Research* 171.
- Osipian, Ararat L. 2023. “Endogenous Economic Growth and Human Capital.” In *Sustainable Economic Growth in Russia*, 43–62. Palgrave Macmillan.
- Perkins, Dwight H., and John P. Tang. 2017. “East Asian Industrial Pioneers.” In *The Spread of Modern Industry to the Periphery since 1871*, 169–96. Oxford Academic Press.
- Porras-Arena, María Sylvina, and Ángel Luis Martín-Román. 2023. “Okun’s Law: The Relationship Between Unemployment and Economic Growth.” In *Handbook of Labor, Human Resources and Population Economics*, 1–20. Springer.
- Schumpeter, Joseph A. 2021. *The Theory of Economic Development*. 1st ed. Routledge.
- Seti, Thembaletu Macdonald, Sukoluhle Mazwane, and Mzuyanda Christian. 2025. “Financial openness, trade openness, and economic growth nexus: A dynamic panel analysis for emerging and developing economies.” *Journal of Risk and Financial Management* 18 (2): 78.
- Shane, Scott, and S. Venkataraman. 2000. “The promise of entrepreneurship as a field of research.” *Academy of Management Review* 25 (1): 217–26.
- Subrahmanya, M. H. Bala. 2021. *Entrepreneurial Ecosystems for Tech Start-ups in India: Evolution, Structure and Role*. De Gruyter.
- The Hindu. 2025. “AI set to add \$15.7 trillion to global GDP by 2030: FICCI-BCG report.” The Hindu Business Line. September 10, 2025. Accessed January 20, 2026.
- World Bank. 2025. “Metadata Glossary.” 2025. Accessed November 19, 2025.
- World Economic Forum (WEF). 2023. “What are ‘gazelle’ companies and why are they essential for growth?” World Economic Forum. 2023. Accessed November 27, 2025.



Green Sill Capital Fiasco: A Recipe for Disaster & Deceit

Anil Kumar Pandey^a

^a*Acharya Bangalore Business School, Bengaluru*

Abstract

An expert in the field of supply chain finance, Greensill Capital successfully brought out uninterrupted financial innovations to meet the demands of its large number of customers' need for financing. In the recent times, the company filed for bankruptcy. This news has put its essential and primary customers, namely, GFG Alliance and Liberty, the metals and trading groups, in danger. These companies have a high growth rate and hence need funds to support such growth. Large amount of funds can be consequentially obtained by converting factorized receivables into securitized package which is an example of financial innovation. To deploy such funds, Greensill needed to find new customers or finance the existing ones. The COVID-19 pandemic further delayed the process. This case throws light over many topics relating to financial strategy and financial instruments like reverse factoring, securitization, insurance, and the relationship with banks. This case also showcases the significance of business ethics. The data presented in this case study is secondary.

Keywords: Financial innovation, business failure, firm growth, working capital management, supply chain finance; securitization, business ethics

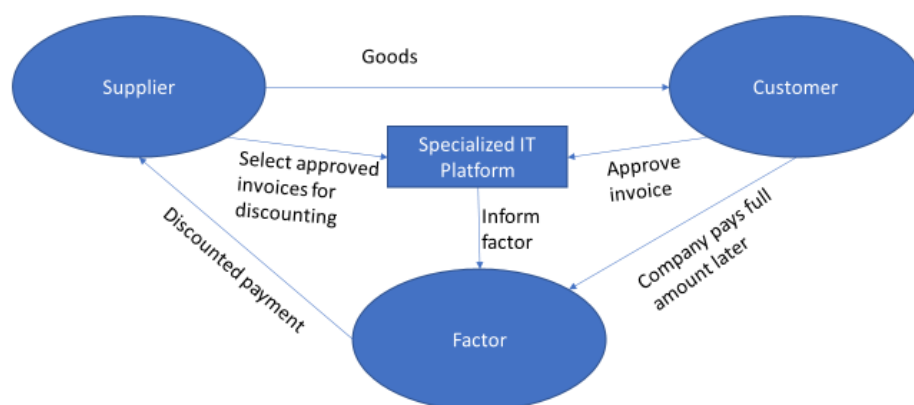
Usually in management studies, case studies of successful companies and organizations are used in educating students. However, it can also be informed by failures that show what should not be done. What is especially interesting are great failures that are often in the news because you learn how they succeeded and why they failed. In this paper, I narrate the story of the collapse of Greensill Capital in March 2021. The importance of this case study is not just because a fast-growing firm broke into bankruptcy. It is also because the report of its growth provides tremendous lessons in strategy, networking, and teaching Alternative Finance for business management students. The final failure highlights that cutting corners is not only unethical, it is also unhealthy for all the supply chain that it was financing.

1. A brief introduction to Alternative Financing

When usually a company starts, it starts with a small amount of capital and assets. As it grows, it requires huge amount of funds. Not only equity, the business also requires debt financing. Unless a substantial amount of collateral security is provided, banks are usually highly unwilling to give a big loan to businesses. Further, fixed assets are required for such collateral and even so, the loan is only provided on part amount of the value of the assets. For example, if a land of 10 lakh rupees is mortgaged, the bank would be willing to give somewhere around 5 to 7 lakhs. The proportion could be higher or lesser depending on how developed the country is. The interest rate on the same would also differ based on different parameters of the country. The availability of such credit funds also affects the working capital management of the organizations and specifically small organizations.

Thus, a financial bottleneck is created and companies which want to grow fast and want to borrow capital for their businesses have a dire need to find a different way of resourcing their finance. Such funding must also put more value to their collateral security. One of many such sources of alternative finance is known as bill discounting, and another by the name of factoring. In bill discounting, the company recovers the money from the costumers at a later date and pays off the bill discounter. In factoring, the factor collects the money. Such services are provided by banks and non-banking financial institutions. While bill discounting is risky free and cheap, on the other hand, factoring has a probability of risk and is expensive, which is because of the extra services provided with the same. It is apparent that if a firm is fast growing, it would require more financing and hence, the firm would even be willing to pay a higher rate

of interest. Many times, the banks provide the factoring services at a lower rate to such large firms for invoices or bills, specifically if such firms have frequent transactions with consumers using an online platform. Since the banks offer such services, they have extremely competitive terms on these services because they get last-mile data to lock customers. But for smaller companies with higher risks, a non-banking factor, like Greensil Capital, is needed. The insight that large customers are less risky has led to the development of reverse factoring, where the acceptance of bills by large customers provides immediate finance to suppliers. As we can see in the Figure 1, a centralized electronic platform provides all the suppliers with a reverse factoring facility. For discounting the bill, the supplier has to merely log in and select the bills that are approved. Immediate payment is assured to the supplier and this could also give them long term credit. Supply chain firms find this arrangement significantly profitable, and even more so if there are frequent transactions and a wider and greater network size since it reduces the transaction costs. It is also a factor in the growth of supply chain finance at double digit rates. Experts and researchers also say that supply chain management helps the firms to perform better and would further improve if a digital platform is used. This system also helps in reducing the bankruptcy in the market and helps to stabilize the supply chain. In fact, substantive amount of research now says that since supply chain financing decreases the cost of capital by keeping in mind the least risky firm in the chain, which is often times the buyer, it not only helps the individual firms but the whole supply chain group as well. For a firm to perform better, it should be more central to its supply chain but the relationship is an inverted U as returns decrease after an optimal centrality of the focal firm. U as returns decrease after an optimal centrality of the focal firm.



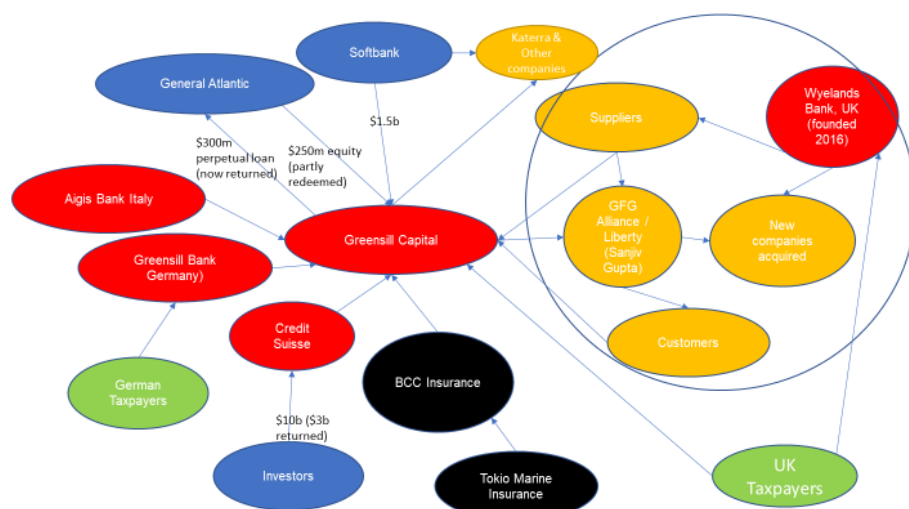
Source: Ashta, 2021, June 27th

Figure 1: Supply Chain Finance, Source: Author

Lower cost of capital of the buyer of the customer is the main factor in determining the use of factoring or reverse factoring. Sufficient research in supply chain finance states that if bankruptcy causes any disruption in the supply chain all the members' risk will increase. But more so if the supplier defaults. (Gibilario & Mattarocci, 2019). However, there is no research on the causes or effects of a failure of the factoring firm on the supply chain. The failure of Greensill provides an interesting case study in this research gap.

2. The Greensill – GFG case study

In Figure 2, we can see the relationships between the major actors of this case study, but latest news states that the repercussions wider. There are two major firms involved in the Greensill debacle. Greensill capital is the first amongst them and it is also the factor. It had many customers, Vodafone and AstraZeneca among them, but the important relation was with Liberty and GFG Alliance. The latter two were a part of Sanjeev Gupta's empire. Simply put, GFG was a customer of great significance and thus all of its suppliers were eligible for reverse factoring or supply chain finance services from Greensill. In short, the payables of GFG were managed by Greensill. And if GFG acquires other firms, their erstwhile suppliers will get an assured source of financing for their supplier payments. This availability of finance would then reduce their risk of insolvency and avoid disruptions in supply chains (Cavenaghi, 2013). To point out something amusing, the primary focus of GFG Alliance is on metals since Zhang et al. found that the industries that gain the most through supply chain finance are mining, manufacturing and transport. This also helps to reduce bankruptcy.



Source: Ashta, 2021, June 27th

Figure 2: A panoramic view of the actors involved in the Greensill Capital case study.

To facilitate its growth, GFG had an external growth strategy through which it acquired other firms. This acquisition strategy was based on figuring out and finding firms with good health but no access to finance. Thus the targets and the targets' suppliers obtain more liquidity by acquiring them and providing them access to Greensill Capital. For example, 0057hyalla steelworks, a failing firm in Australia, was bought by Sanjeev Gupta for A\$700m. The firm paid late and told its suppliers to take financing from Greensill Capital at a 8% discount (Smyth, 2021).

As research had pointed out, the operating performance of the central firm in a supply chain improves till an optimal point is reached (Carnovale & Yenyurt, 2015). In its network, GFG was the focal firm. Thus, the network relationship between Greensill, GFG, and its future acquisitions was an essential part of the strategic relationship.

3. Lowering risk? Private equity, private placements and network externalities

Because Greensill wanted to take advantage of GFG and all its customers, it itself needed finance as well. Partly, it wanted equity since it does not have to be repaid in case of bankruptcy and is therefore considered lower risk. It took this equity funding through private placement, another alternative finance arrangement that avoids disclosing information to the market. The technology and high-growth-oriented private equity firm General Atlantic provided Greensill Capital with \$250 million in equity in 2018 (Smith, Wiggins, & O'Murchu, 2021). Based on this increase in equity, Greensill itself could take more debt. Simultaneously, General Atlantic was happy because a year later, in 2019, General Atlantic took a perpetual debt of \$300 million from Greensill (routed through a chain of companies).

Moreover, for Greensill, this led to another dynamic advantage. Since General Atlantic had invested in Greensill, other investors felt that the due diligence performed on Greensill was adequate, and therefore, in 2019, Softbank's Vision Fund invested \$1.5 billion into Greensill (Smith, Wiggins, & O'Murchu, 2021). Moreover, by joining Softbank's network, Greensill could get introduced to all the large firms that Softbank had invested in and could factor their invoices (Jenkins, 2021). Moreover, Softbank was willing to invest in Greensill to indirectly bail out its own target acquisitions that were having trouble, such as Kattera (Inagaki, 2021).

4. Financial leverage to increase returns

However, equity capital, such as the founders and the private equity funds, wants to have the financial leverage to increase their returns. For this, Greensill Capital needed to get refinancing from a bank or some alternative finance sources. Partly, it was able to get some refinancing from Greensill Bank AG, a local bank in Germany that Greensill had acquired, for its fixed assets such as private aircraft. It turned to Credit Suisse and GAM for much larger refinancing, and they decided to find investors who would lend money. For this, they needed to create a securitization-type fund for Greensill receivables that investors could buy into (Jenkins, 2021).

5. Insurance for risk mitigation

Investors like low risk. Since Greensill's business with GFG was risky, it was important for Greensill to find insurance for the bills that they were discounting. This insurance was essential if Greensill wanted to get refinanced by securitizing the customer bills and packaging them, and selling the package to investors. If the package proposed by Credit Suisse on Greensill receivables were insured, the investors would be willing to invest in such structured funds because their own risk would reduce. In our case, the insurance was provided by BCC insurance, certified by one of this insurance company's brokers in Australia. The outcome of this financing from Credit Suisse meant that suddenly Greenfield was flushed with the availability of funds to on-lend and could grow immediately if it could find customers. This meant that Greensill required its customers, such as GFG, to grow quickly to access the suppliers of all their acquired companies. Since GFG wanted to grow also, it became a convenient partnership. Moreover, the insurer would also grow if the size of the portfolio it insured grew. Another win-win-win situation. By 2021, the Greensill linked funds were about \$10 billion (I. Smith, 2021).

6. The problem: Overexposure was the key risk

The problem was that GFG was a big part of Greensill's portfolio and as both grew, the percentage part of the Gupta empire in Greensill became about 70% by 2019 (Smith, Wiggins, & O'Murchu, 2021). By March 2021, GFG had borrowed about \$5 billion from Greensill (Smith, Barnes, Hammond, Smyth, & Pooler, 2021). Moreover, COVID-19 had deeply affected the metals business since all the downstream customers were affected, thus fragilizing the GFG alliance and its suppliers and increasing their need for financing. At the same time, COVID-19 had reduced bank financing and therefore the supply chain was even more

dependent on the funding from Greensill. Greensill could behave in a risk neutral or risk seeking manner, since it had insured the portfolio of discounted bills, thus exploiting a situation of moral hazard (Stiglitz, 1983).

Since Sanjeev Gupta's financing for his external growth was quite opaque, it meant that Greensill funds' portfolio seemed increasingly risky to outsiders. The BCC insurance company was fearful but still interested because its own growth depended on the development of the network. However, when another insurance company, Tokio Marine, acquired the BCC insurance company in April 2019, the acquiring company examined the entire portfolio of BCC Insurance. Notably, it felt that BCC's exposure to the Greensill fund was too high and that Greensill's exposure to GFG was too high, and that GFG was too opaque to determine risk. Moreover, a part of the package pertained to future expected bills of GFG which were therefore risky. Tokio Marine, therefore, stopped the insurance cover for the Greensill fund (I. Smith, 2021).

7. Bankruptcy

When the insurance stopped, the investors realized that the risk had gone up, and they asked to get their money back unless a new insurance company could be found. However, no insurance company was willing to take the risk primarily because they felt that Greensill Capital was too risky and because the GFG empire was also too foggy. Notably, when a firm is dealing with closely held companies, they can raise invoices on each other purely to get supply chain financing from different factoring firms (Smith, O'murchu, & Pooler, 2021). As a result of the lack of insurance, investors wanted their money back, and Credit Suisse, in turn, had to ask Greensill to pay back. This reimbursement required all the GFG suppliers to pay back, which they could not do. GFG itself had used the money to buy fixed assets (that is, companies), and therefore, it was not possible to divest them quickly enough. Moreover, the COVID crisis had reduced the sale of metals and had impacted Sanjiv Gupta's business adversely, and he had already defaulted on payments of about \$1 billion (Smith, Barnes, et al., 2021). Public subsidized loans from the UK government went through Greensill to GFG.

The result was a liquidity crisis that caused Greensill Capital to file for bankruptcy administration on March 8. This bankruptcy then impacts investors and Credit Suisse upstream, GFG, and its suppliers downstream. As noted earlier, the manufacturing, mining and transport industries are found to be more dependent on supply chain financing for the survival of the chain members (Zhang et al., 2019) and therefore the closing of the finance impacts the whole

supply chain of GFG. In Germany, the Greensill Bank was also asked by German regulators to reduce their exposure to GFG Alliance (R. Smith, 2021). In Italy, Aegis bank also suffered from the failure of Greensill and has failed (Smith, Wiggins, & Borrelli, 2021).

It also affects its shareholders, such as General Atlantic and Softbank. General Atlantic had redeemed some of its share capital when Softbank invested and was therefore much less exposed. To reduce its reputation damage, it has repaid the \$300 million perpetual loan so that the downstream investors and banks reduce their losses. The investors have been able to get back \$3 billion of the \$10 billion invested in the Greensill fund.

GFG Alliance is therefore left without financing and a number of downstream financiers, such as Credit Suisse are asking it to reimburse them. GFG has also been unable to make its tax payment to the government (Pooler, Robert Smith, and, & Pickard, 2021). German taxpayers are affected since the German court has also started examining the winding up of Greensill Bank, since it had lent to GFG also, and the State would have to repay the retail depositors upto €100,000 each.

8. Conclusion

The Greensill case serves as a contemporary teaching platform to examine how modern firms increasingly compete, grow, and fail through financial design rather than through products alone. Its pedagogical strength lies in integrating finance, strategy, and ethics into a single narrative of organizational rise and collapse. For management scholars, the case opens pathways to theorizing financial fragility as an organizational outcome. For managers, it underscores that the durability of any business model ultimately depends less on innovation itself than on the transparency, discipline, and integrity with which innovation is governed.

References

- Ali, Z., Gongbing, B., & Mehreen, A. (2020). Does supply chain finance improve SMEs performance? The moderating role of trade digitization. *Business Process Management Journal*, 26(1), 150-167.
- Ashta, A. (2008). Sustainable growth rates: refining a measure. *Strategic Change*, 17(5/6), 207-214.
- Carnovale, S., & Yenyurt, S. (2015). The Impact of Supply Network Structure on the Financial Performance of the Firm. *Supply Chain Forum: International Journal*, 16(3), 18-28. doi:10.1080/16258312.2015.11716349
- Cavenaghi, E. (2013). Supply-chain finance: The new frontier in the world of payments. *Journal of Payments Strategy & Systems*, 7(4), 290-293.
- Chen, C., & Kieschnick, R. (2018). Bank credit and corporate working capital management. *Journal of Corporate Finance*, 48, 579-596.

- Gibilaro, L., & Mattarocci, G. (2019). The impact of corporate distress along the supply chain: evidences from United States. *Supply Chain Management*, 24(4), 498-508.
- Higgins, R. C. (1977). How Much Growth Can a Firm Afford? *Financial Management*, 6(3), 7-16.
- Hofmann, E., & Zumsteg, S. (2015). Win-win and No-win Situations in Supply Chain Finance: The Case of Accounts Receivable Programs. *Supply Chain Forum: International Journal*, 16(3), 30-50.
- Inagaki, K. (2021, June 24, 2021). SoftBank founder grilled by investors. *Financial Times (Europe)*.
- Jenkins, P. (2021, March 29). The echoes of Enron in Greensill saga. *Financial Times (Europe)*.
- Morris, S., Kinder, T., Walker, O., & Smith, R. (2021, April 21). Credit Suisse bitten in 'swim with sharks'. *Financial Times (Europe)*, p. 7.
- Pfeifer, S., O'Murchu, C., Dickie, M., & Smith, R. (2021, April 26, 2021). How Gupta sold green revolution to politicians. *Financial Times (Europe)*.
- Pfeifer, S., & Walker, O. (2021, May 25/2021). Gupta seeks to sell three UK steel plants and settle debt. *Financial Times (Europe)*.
- Pooler, M., Robert Smith, and, S. P., & Pickard, J. (2021, March 9). Sanjeev Gupta's metals businesses miss UK tax payments. *Financial Times (Europe)*.
- Smith, I. (2021, April 8). Greensill's demise turns spotlight on Marsh. *Financial Times (Europe)*.
- Smith, R. (2021, April 7). Lex Greensill assured staff of 'enormous' liquidity before collapse. *Financial Times (Europe)*.
- Smith, R., Barnes, O., Hammond, G., Smyth, J., & Pooler, M. (2021, March 19). How Sanjeev Gupta lived large on the back of rickety financing. *Financial Times (Europe)*.
- Smith, R., & Hume, N. (2021, June 3, 2021). Trafigura warned Credit Suisse over suspicious Greensill Gupta invoice. *Financial Times (Europe)*.
- Smith, R., O'murchu, C., & Pooler, M. (2021, April 24, 2021). Greensill saga shines spotlight on 'friends of Sanjeev'. *Financial Times (Europe)*.
- Smith, R., & Storbeck, O. (2021, June 24, 2021). Greensill's Covid loans went to Gupta businesses. *Financial Times (Europe)*.
- Smith, R., Wiggins, K., & Borrelli, S. S. (2021, May 25/2021). Italian bank fails over Greensill exposure. *Financial Times (Europe)*.
- Smith, R., Wiggins, K., & O'Murchu, C. (2021, March 25). General Atlantic: the revered tech investor that backed Greensill. *Financial Times (Europe)*.
- Smyth, J. (2021, May 4, 2021). Gupta's 'spiritual home' left on edge by crisis. *Financial Times (Europe)*.
- Stiglitz, J. E. (1983). Risk, incentives and insurance: The pure theory of moral hazard. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 8(1), 4-33.
- Taleb, N. N. (2010). *The Black Swan: the impact of the highly improbable* (Second ed.). London: Penguin.
- Walker, O. (2021a, May 29, 2021). C Suisse compliance chief was warned about Gupta. *Financial Times (Europe)*.
- Walker, O. (2021b, April 5). Supply-chain finance: a new spin on a prehistoric idea. *Financial Times (Europe)*.
- Wu, Y., Wang, Y., Xu, X., & Chen, X. (2019). Collect payment early, late, or through a third party's reverse factoring in a supply chain. *International Journal of Production Economics*, 218, 245-259.
- Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y., & Xu, Y. (2018). Supply chain finance: A systematic literature review and bibliometric analysis. *International Journal of Production Economics*, 204, 160-173.
- Zhang, T., Zhang, C. Y., & Pei, Q. (2019). Misconception of providing supply chain finance: Its stabilising role. *International Journal of Production Economics*, 213, 175-184.
