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Research Article

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BANKRUPTCY REORGANIZATION OF SMALL FIRMS: ASSET SPECIFICITY OF INSOLVENT FIRMS

by

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Abstract

An insolvency regime encourages efficient resolution of healthy firms on a going-concern basis rather than liquidation. This paper evaluates the post-resolution outcome of small insolvent firms in a recent filings dataset year of 2024. It relates the outcome to information asymmetricity, misclassification, and inefficient mechanism leading to value loss of viable firms. It constructs a firm-level asset specificity index using three components of standardization, durable life, and re-usability. It introduces the index in a value loss model and finds that the index's significance in explaining the nature of value loss. It covers losses to liquidated amount, re-sale amount. The robustness tests involve evaluating the total errors after reclassifying the resolved firms assigning new tags. We find significant reduction in value losses and improvement in recovered amount. The implications pertain to improved ex-post efficiency and objective assessment and value preservation of small bankrupt firms for all stakeholders.

Key words: valuation, resolution, asset specificity, model

Introduction

During the past few decades, the legislative reforms towards bankruptcy resolution has evolved across the globe. Dewaelheyns and Van Hulle (2009) mention major countries in Europe (e.g., UK, Germany, France, Italy, and Spain) periodically reformed their bankruptcy legislation. The reforms are aimed at building public confidence in systems, boosting investor confidence, and maintaining efficient markets.

Critics highlight the role of both debtor-friendly and creditor-driven regimes. The traditionalists argue bankrupt firms are fixed amicably to continue as a going concern that maximizes value for all stakeholders. Conversely, the proponents of value preservation argue for ultimate liquidation of firms to satisfy all claimants and direct stakeholders (employees, vendors, third parties, governments, lenders, and owners).

The insolvency frameworks mandate a public platform of collective bargaining mechanism to achieve an open and transparent outcome for bad assets. Further, in the creditor-paced approach, a legally appointed "Committee of Creditors" conducts the adjudication of genuine claimants made to achieve fruitful results. In reality the complexity of multi-stage decision cycle cause empirical challenges of time delay, outright haircuts, disputes, counter-litigations, and eventual low recoveries.

Celentani et al. (2010) mentioned that creditors solely aimed to maximize their self-interest in the banker-driven model. Alternatively, stakeholders aim to maximize the firm's going-concern value in the debtor model to safeguard the interests of all agents.

The reorganization cycle should effectively turn sick firm into active firms. A functional firm with a premature "bankrupt" tag, will curtail business relations, customer confidence, and failure of the supposedly viable entity. Therefore, ex-post resolution efficiency of firms under this regime is of interest to practitioners, academia and policy professionals.

The resolution activity undergoes controversies. First of all, the inside owners and promoters of small firms would vehemently oppose creditors' attempt to absolve them from direct ownership of their own creation. The multi-state legal process aims to eliminate information barriers to avoid wrongful misclassification of viable firms as non-viable.

There could exist misclassification errors in defunct (liquidate) and non-defunct (going concern) firms. Information asymmetry could lead to undervaluation of the firm's assets and increase the chances of liquidation rather than resolution. When there are information barriers, creditors have an incentive to choose liquidation rather than reorganization. In numeric terms, it translates to delay, poor recovery and many times faulty classification of feasible/infeasible filings.

A value loss occurs when the firm's sale value is less than the realized firm value. The value error is the difference between the small firm's projected future earnings and actual post-resolution re-sale amount or liquidation amount from its assets. The disputes over the validity of specific assumptions could cause a fair value loss of the firm.

Unlike many developed markets, the developing economy of India implemented the IBC only in the year 2016 following the UK's creditor originated model. The Indian Insolvency Code (IBC, 2016) provides a creditor-led approach to the reorganization. Over a decade, the series of amendments to IBC has gradually improved the legislative results. Specifically, time delay and the chances of cross-litigations but not the recovery rate of the small firms' assets. Ex-ante, under the insolvency code (IBC), when a filing is tagged as defunct it translates into liquidation. Since the situation for defunct firms could be different from that of non-defunct (active) firms, an academic study should explore the sources and causes of the associated inefficiencies.

Few authors revealed faulty classification of firms across different countries (Adalet McGowan et al. 2018; Banerjee and Hofmann 2018). Few authors (Lemmon et al., 2009; Balcaen et al., 2011; Fischer and Wahrenburg, 2012) mentioned not all US firms are termed viable in a bankruptcy proceeding. Few studies on bankruptcy resolution by authors (White, 1984, Campbell, 1994;, Bryan et al., 2008;, Jacobs et al., 2012) suggested the early signals of resolution and the firm's bankruptcy. White (1994) mentioned three types of efficiency over the bankruptcy cycle, ex-ante efficiency, before the filings, process efficiency (e.g., speed, cost, delay and hidden costs, etc.) and ex-post efficiency, firm's future after the filing. The interest remains in the small firms' future outcome after the filing.

In the debtor-friendly model, viable firms are revived, which could lead to high ex-post resolution inefficiency (Fernández, 2004). Gennaioli and Rossi (2010) find a creditors-friendly process provides higher efficiency, attributed to firms' internal characteristics, ownership, and management quality (Thorburn, 2000, Fernández, 2004). Lemmon et al. (2009) and Fischer et al. (2012) suggest that insolvent firms have a higher likelihood of becoming viable in financial bankruptcy.

Wahrenburgh (2012) associated the causes of bankruptcy with the firm's profitability and advantage. Lemmon et al., 2009) mentioned economically bankrupt firms have little or negative operating earnings, and are incapable of being a living entity.

Weak insolvency regimes prevent lenders to amicably settle (liquidate) or restructure insolvent firms. Becker and Ivashina (2023) mention that weak regimes lead to delays, increased costs, and uncertainty for creditors, discouraging them from liquidating insolvent firms . García and Sanguinetti (2012) suggests that a strong regime benefits all stakeholders characterized by lower cycle time, lower costs, and higher rates of credit recovery

This paper contributes to address the limitation of IBC regime by identifying and proposing a fair value framework for unresolved assets to improve the accuracy of firm value. This paper incorporates quasi-complete information (firms' properties) to reduce the small firm's value loss to achieve a favourable outcome.

IBBI (2025) reports corporate insolvency cases fell by 28% to 724, with recoveries still low (70%) of the admitted claims, and an average haircut rate (67%) in the year 2025. A positive haircut rate (>0) implies direct loss to all

stakeholders and the firms' value. Further, during 2025, a cumulative number (8,308) of companies that filed bankruptcy were resolved (61%). Similarly, a good number of resolutions (1926) were legally approved (14.3%). IBBI (2025) reports a cumulative recovery rate (33%) for the resolved firms (1926). This is better than a low-resolution rate (4.3% only) in the previous year (IBBI, 2024). However, the total liquidated amount (INR 45.80 Billion) is miniscule against a total admitted claim (INR 1064.69 Billion). Overall, the public concern remains in parameters of the small firm's ability to satisfy the Distributed Amount Liquidation Value, Sale Proceeds, andare significantly lower compared to the Amount of Admitted Claims.

This work reviews most significant empirical hypotheses and derives the fair value of assets, suggesting recommendations for creditors, policymakers, resolutions professionalisms and legal implementation. Restructuring may not be possible when the firm's value under restructuring is higher than a bankruptcy sale. Post facto resolution favors larger size firms profitable. Since insolvency is costly, the tradeoff between the loss aversion and aversion leads to optimal equilibrium outcome.

Possibly, the creditors could have the information on the small firm's existing value is higher than its bankruptcy sale. In our model, we introduce additional conditions required for higher efficiency. Finally, we discuss how these results are connected to the rights of creditors in India.

It contributes to the debate in two significant ways; first, it fills the gap by suggesting a workable model of asymmetric information error. This opens up new avenues of further empirical works on insolvency resolution. Second, it highlights the need for objective diligence before coming to inferences for the sake of claim settlements. This implies both the recovery rate and the small firms' value be maximized to fulfill the total claims and distributed amount.

The first part introduces the ASI index on the inter-commodity matrix to conduct tests of the real input (i-O) expenditures and the real value added outputs by commodity class. The second part tests the value loss in a regression model. The robustness tests incorporate evaluation of the errors and reclassification (cross-tabulation) of the firms (defunct/non-defunct). Later, it concludes with recommendations for the academia, policy makers and practitioners.

2. Literature

Early literature (Modigliani & Miller, 1958, 1963, and Stiglitz, 1974) examined optimal resolution based on both the firm's expected effective cost of capital, and the firms' capital structure. The major aspects of corporate bankruptcy mechanism was highlighted as 1) causes of bankruptcy, 2) determinants of liquidation, 3) costs of resolution and 4) valuation and recovery losses.

The works of authors (White, 1983, Hotchkiss et al., 2008; Senbet et al., 2012). White (1983) signified the impact of US bankruptcy law on accumulated legal costs. Campbell (1996) identified two critical factors; firm profitability and firm size that distinguished between the liquidated (defunct) and feasible (non-defunct) firms. Casey, McGee, and Stickney (1986) found firm's higher assets to debt ratio raised the chances of positive resolution, and higher level of "crown claims" (government, unsecured or third party claims) increased the chances of liquidation.

Casey, McGee, and Stickney (1986) used a matched dataset of bankruptcy files to highlight the distinction between

both dissolved and active firms.

Giammarino (1989), and John et al. (2013) highlighted the consequence of information asymmetry among the creditors, bidders, and public stakeholders in bankruptcy resolution cycle.

Bulow & Shoven (1978) found efficiency loss in US firms that underwent involuntary bankruptcy rather than liquidation as a choice. Gertner & Scharfstein (1991) found coordination problems between stakeholders in the resolution cycle. Giammarino (1989) shows firms end in bankruptcy process with information asymmetry among creditors. The faulty resolution can lead to inefficiencies by choosing negative NPV projects reorganization under bankruptcy procedure. The Public debt holders have the natural choice for a legal bankruptcy resolution.

John et al. (2013) find that, ex ante, firm owners may not choose not to sell their assets, if the firm's equity option value of the high. Mooradian (1994) observed that US bankruptcy laws caused viable firms to land in bankruptcy. Bergström et al. (2002) found well-secured firms (creditors) opposed public attempts of resolution. Blazy & Chopard (2004) showed the presence of bidders' free-riding incentives could result in loss of firms' value and non-optimal outcome.

Rao M R (2024, CAFRAL) emphasized on timely resolution cycle aiming at positive resolution rather than liquidation and value deterioration... IVSC (IVS 104: BASES OF VALUE 2016) suggests that the form's assets' attributes may relate to the relevant physical, geographic, and economic characteristics. Market Value does not always reflect an asset's relevant attributes to all owners in the market. Ordinarily, the valuation method for insolvent firms could be based upon the expected cash flows from its supposedly forgone (extinct) operations. Valuation also includes factors such as expected capital costs, comparable performance of entities, existing advantages, etc. The actual price realized may be higher or lower than fair value, depending on the distress situation, competitive bidding, or the nature of the business's claims. There does not exist an empirical approach for fair value projections for a defunct firm treated as a going concern (on an imaginary basis).

The status of the evolving regulatory landscape plays an important role in terms of associated transaction and compliance costs on the industry (e.g., certification, licensing, regulatory approval, amended land laws, direct or indirect tax rules,etc.c).

Here comes the role of secondary markets in the rescue of stressed assets. A well-developed secondary market provides the necessary depth and breadth to facilitate the exchange of stressed assets through a widely held auction with open and full-fledged participation from a large number of bidders. Such a market for the firm is fixed or durable assets (P&M, L&B) would attract many bidders and enhance generic use in a given industry (e.g., transport goods, airlines). Few works have explored the benefit to producers from manufacturing durable goods in the context of a circular economy, including the potential for resale price premiums. Firms manage to retain the goods' resale value in secondary markets via specific benefits (repair, reuse, and retrofitting, reassembling) associated with market loyalty and brand attractiveness. Hendel and Lizzeri (1999, 2003) argued that secondary markets could ensure higher profits

for manufacturers based on their study on producers from secondary markets for durable goods. Hendel and Lizzeri 1999) analyzed how secondary markets and adverse selection affects the pricing and trade of durable goods.

Instead, used-good ownership was random, they argued that consumers self-select into buying new or used goods based on their preferences. That even with severe information asymmetries (where sellers know more than buyers), the used-good market never shuts down and trade volumes remain substantial.

They argued that manufacturers might benefit from adverse selection because it can lead to higher new-good prices. They found "unreliable" brands experienced were cheaper than the known branded goods

Hendel and Lizzeri 2003), argued manufacturers interfere with secondary markets through various strategies, leasing, privy spares, maintenance restrictions, or specific rental policies to control the supply of used units. They found that durable manufacturers prefer to alter or reduce the durability of a product rather than "call back" since the secondary active used market can support higher initial sales prices. For example, "lease-only" policies was used by manufacturers to compete against the resale market (the Coase effect).

Hendel and Lizzeri's (2003) stressed on maximizing the firms asset's resale value. Chen et al. (2013) explored how firms could benefit from secondary markets. The potential for a price premium on durable products is driven by consumer demand for long-lasting, repairable, and upgradeable items. The secondary market for repairing, reusing, and remanufacturing durable products is a critical component of the circular economy.

James et al. (2014) highlighted that the firm's asset attributes (mobility, durability, and standardization) accounted for the industry-level (plant & machineries) variations in recovery rates. Few studies explore the effect of asset specificity on liquidation value within an industry (Pulvino, 1998; Gavazza, 2011; Ramey and Shapiro, 2001; Campbell et al., 2011). Acharya et al. (2007) demonstrated that the specificity of corporate assets negatively affected debt recoveries in the US corporate debt market during industry and firm level distress.

James et al., (2014) developed an index of "specificity" based on three main characteristics of mobility, durability and standardization. Vishny (1992) found a negative relationship between asset specificity and industry-level distressing the value of insolvent firms. Mobility is the industry level ratio of transportation cost to total production cost. Durability is the average depreciation rate of all commodity assets as calculated from input-output transaction tables. The long durable assets (low depreciation rate) are the machinery, power transmission systems equipment, and sewage systems. Fixed assets with the lowest durability (highest depreciation rate) include computers and office equipment. Higher durable (low depreciation rate) are wagons, rails, loco motives.

Customization involves higher design costs (or imported machinery). Vishny (1992) predicted a negative relationship between industry-level asset specificity and industry-level distress on insolvent firms' value.

Research Questions and Hypothesis

Prior literature has mainly investigated the differences between zombie and good firms by using observed financial data (cash flow, turnover, debt levels). Prior works highlighted extensively the causes of Failure of defunct firms (Argenti 1976; Weitzel & Jonsson 1989; D'Aveni 1989; Laitinen 1991, 1993; Ooghe & De Prijcker 2008; Laitinen & Lukason 2014). Howver except for Campbell (1996), and few others ( ) the works on non-defunct firms are limited. This study will contribute to the previous reorganization literature and examine the assymetricity aspects related to the firm's assets. The efficiency was examined for voluntary reorganizations (see Smith & Graves 2005) but rarely for legal reorganizations (see Routledge & Gadenne 2000, 2004; LoPucki & Doherty 2002; Laitinen 2008, 2011).

The question of resolution efficiency of defunct firms needs exploration. The outcome is acceptable when the problem of adverse selection is addressed by identifying inefficient firms accurately and made defunct (liquidated). A well chosen and recent sample of resolved firms e.g. The Indian IBBI system) can help investigate the determinants of value loss. Specifically, we focus on the influence of the broader firm level factors (asset specificity) on the post-resolution efficiency of insolvent firms.

The goals of Fair valuation depends on making relevant assumptions about cash flow projections from operations, and the cost of capital. There is no directly applicable empirical model for valuing stressed assets available in the literature. Since the reuse, (Second-Hand Market) Value depends on Product Specifications, Age, and Conditions manufacturers should consider the second-hand market value early in the design stage to remain competitive. The circular economy principles (SDG Goals S13, UNEP) favor repairing, reusing, and remanufacturing, which enhances the product's lifespan in the presence of a secondary market.

The review evidence does not confirm strong inferences on the impact of insolvency as to minimize efficiency (total errors). Benmelech et. al., (2005) holds that firms with high re-deployable (low specificity) assets would find easier borrowing terms from lenders, longer maturity, low cost external financing, convenient terms, etc. if there are Financial constraints on the firm then higher levels of asset specificity could put severe limitations during the legal solution.

Campbell, S.V. (1996) suggested both firm size and profitability positively influenced the positively resolved outcome. The volume of admitted claims reflect the size of the firm. Both the tangible and intangible value of the firms, are influenced by the volume of admitted (raised) claims by stakeholders on the firm, Since, the valuation losses could be impacted by the volume of admitted claims, the intangible value of the firm could be a significant component. Subramanian et al. 2011) mentioned that the firm resorts to risk equity fund channels rather than debt channels when the firm has "specific" collaterals. As mentioned, there are demand-driven factors, such as inflation, that may affect the resale prices of assets. Technological shifts in the conversion of inputs (e.g., I-O coefficients and the; transition towards renewable, could also cause an impact on firm value. Similarly, supply-driven or macroeconomic factors, such as wholesale prices (WPI), exchange rates, and the cost financing rates, as well as labor wage costs, are also important. For example, during industry-level distress, the asset specificity hypothesis argues that the transaction price of a firm comprising specialized assets would remain lower than its fundamental value.

The misclassification errors or selection errors are of two types: Type II errors involve tagging defunct firms as non-defunct, and Type II errors involve non-defunct firms as defunct. The total errors are the sum of Type I and Type II errors.

We aim to arrive at the combined efficiency of the insolvency cycle to the last mile stakeholders who bear the final loss and low recovery rates due to higher positive total errors (type + type ii).

The national courts (e.g., NCLT) may resolve liquidation when the resolution process fails without a viable plan for revival of the firm. Under thick, such a company, once within the resolution process, is tagged as defunct, which translates into liquidation. Since the situation for defunct firms may differ significantly from that of non-defunct (active) firms, we distinguish between the two types of defunct firms (yes or nos.

The null hypotheses are described below;

H1: A well-developed buyers' market is essential to obtain a resale value of "specific" assets.

H2: there are no misclassification errors in the IBC resolution process

H3: High asset specificity affects firm value.

H4: Asset Specificity Index improves the resolution efficiency of bankrupt firms.

Conceptual framework.

Giammarino (1989) and John et al. (2013) highlighted the presence of information asymmetry among the creditors, bidders, and public stakeholders in bankruptcy resolution cycle. A bankrupt firm that shows higher "free assets", lower debt to assets or lower "total claims" passes the test of reorganization. Liquidation is evident when it has negative net worth. The test of mis-classification incorporates the degree of asymmetric information.

In circular economy and sustainable literature, firm's assets are characterized by acquisition, installation, maintenance and disposition. The Value of plant and machinery or physical assets on a standalone basis is different from Liquidation Value of the firm in whole. Standard branded capital goods of make and model would fetch a Good resale prices across a wide spectrum of industries. However, oil and gas mixtures, immobile bins, storage tanks, perishable chemicals, etc., would have a limited number of buyers. For example, non-perishable intermediary goods are or commonly used raw material, fuel inputs in the manufacturing industry can fetch a resale value. For example, service infrastructure or construction sectors include road and buildings, aerodromes, bridges, tunnels, pipelines, ports, harbors, runways, waterways, hydroelectric projects, etc. the service sector's collaterals; Hotel buildings, furniture and fixtures, restaurants, boarding and lodging houses, eateries, etc. For example, transport industry assets are highly mobile (e.g., used cars, aircraft, ships, vehicles), which can fetch many buyers easily. Land & Building, Pure real estate, immovable properties, residential buildings, and commercial properties assets are disposable to buyers. The high mobility (low transportation cost) are water transport and air transport assets. Industries with the lowest mobility (high transportation cost) are service sector assets, hotels, restaurants, and utility pipelines.

Durability is the book life (years) of an asset. The country specific tax authorities (e.g., Income tax act amended Finance Bill, 2024) provides depreciation rates for major asset classes (e.g., Building and hotels (10%), Furniture, fittings & electrical installations, (10%), older Plant & Machinery (before April 1, 2020) (30%), new P & M (15%), Computers& software (40%), Intangible assets (25%).

Custom assets have a longer expiry life (e.g., knowledge asset). The legal life of a granted patent license is maximum of 20 years in India (Indian patent act 1971). In the Construction industry, firms incur fixed costs (onetime costs on installation) on concrete ready mix plants (non-transferable), concrete pillars, which are dismantled on work completion at borrower's cost.

Methodology

There are two parts in the analysis. In the first part, we conduct tests on the Chi-Square Tests of the Difference between the Input and Output Values (2007-18, 2015-16) by incorporating the inter-commodity matrix. The second part conducts regression analysis of the value loss and distributed loss. The robustness of the results are validated with

significance tests of the correlated ratios. The analysis with the sample dataset of resolved firms and the preparation of input-output share matrix.

Loss types

The Loss from distressed sale (= Liquidated firm value and Sale value. Loss is the difference between quoted value (liquidated value) and market value. The “distributed loss" is the difference between the total admitted claims and the total realized re-sale value of the firm. The haircut (loss) is the difference between a firm's admitted debt loan amount and the distributed amount.

Input- Output Table

The input-output table (commodity x industry matrix) gives the inter-industry transactions values at factor cost. The columns in the I-O table represent the industries and the rows as the principal products (commodity groups).

The Absorption (commodity x industry) matrix and the Make (industry x commodity) matrix provide the commodity-to-commodity movement data, and industry-to-industry flows. The absorption and make matrices are interpreted with fixed technology (i-o coefficients) assumptions. The coefficient matrix is obtained by dividing the input column cell values by the industry outputs from the matrix (commodity x industry).

The make coefficient matrix is obtained by dividing the output row cell values by the respective industry outputs. The market share matrix is derived by dividing input column cell values by the respective commodity row outputs. We generate a matrix of asset specificity for the (12 x 12) of the (I-O) industry-industry commodities (see Table A1 in the appendix).

WpI

Each year the ministry (DPIIT, 2024) releases WPI index for over 500 major commodities. We map and incorporate the new WPI series (2011-12) data into a vector of (12 x 1) commodities. We create the price index vector (12 x 1) from the available WPI series for all three years, 2007-08, 2015-16, and 2024-25. We prepare the WPI vector (12 x 1) sub-aggregated for three different periods 2007-08, 2015-16 and 2024-25, we create a price index vector (12 x 1) from the available WPI series for all three years, 2007-08, 2015-16, and 2024-25.

The elements of the basket of WPI series is the superset of the elements (aggregated eight sectors) of the Input-Output Transactions table. Therefore, a mapping between the complete WPI basket (about 500 items) and the standard I-O table (about 130 items) is necessary. The exercise of mapping both the sets could be a compromise on the accuracy or the granularity of the actual product-market shares of the intensity of commodities.

Asset Specificity index

We extend the framework in Gavazza (2011) and Bernstein, Colonnelli, and Iverson (2019). Kim and Kung (2017) computed specificity as the complement of redeploy ability, which is a proxy for the number of industries using a “particular” type of asset. Higher usability of an input implies greater re-deployability across industries. The overall effects of changes in one sector such as an increased usage of a commodity will affect the industries supplying its components on other sectors.

We create The Asset Specific Index (ASI) from three sub-indices (1) Re-deployability, (2) Durability and (3) Custom, using two standard formula the simple mean and the geometric mean discussed in the literature (Fisher, 1976, Laspere, 1986), as below;

Asset Specific Index (simple average),

$ASI_{AVERAGE,}$ i, t = {Ri,t +D i,t + CI, t} / 3 (1)

O*r alternatively,*

Asset Specific Index (geometric average),

$ASI_{GEOMETRIC}$ = {Ri,t x D i, t x C I, t}} $^{1/3}$ (2)

Where i, is the sector of the input commodity, which comprises 12 sectors (e.g., Construction, durable services, electricity, food, fuel, manufactured goods, manufactured food, mineral, non-food, services, textile, transport, etc.).

Where RI, t, D,i t, and C I, t are the three components of (1) Re-deployability, (2) Durability and (3) Custom, and are explained below.

(1) Re-deployability, Ri, t= xi,t/∑xj,t

Where, xjt is the I-O share of the commodity, which is the product of I-O coefficient and the value of output for the period t.

The I-O TABLE input coefficient (a_{ij}) shows the quantum of commodity i that is required to produce a unit of output in sector j. The COEFFICIENT (a_{ij}) is determined by dividing the value of the flow of commodity I to the sector j by the total output of the receiving sector. A higher coefficient for a specific input indicates higher degree of its re-deployability in the linked (associated) industry's production output.

For each commodity, at a granularity of the industry code (three digit), the re-deploy ability index is constructed as the ratio of the number of industries that used the commodity and the total number of sectors.

We incorporate the I-O table transactions dataset to compute the shares from the commodity-commodity matrix as below;

aij = aij/∑ aij, t

Where aij is the proportion of the commodity input usage of commodity “I” by commodity output “j”.

The input and output values are deflated to constant prices using GDP deflator. aij ranges between (1/n) to 1.

(2) Durability

Durability Di, t = (100- Depreciation Rate, I, t %)

Where i is the commodity asset and t, is the time in years.

Where Depreciation Rate (I, T) is the book life of an asset under INCOME TAX ACT. Higher depreciation rate implies lower durability of the asset. The Income tax act (amended Finance Bill, 2024) provides depreciation rates for Building and hotels (10%), Furniture, fittings & electrical installations (10%), older Plant & Machinery (before April 1st, 2020) (30%), new P & M (15%), Computers & software (40%), Intangible assets (25%), respectively.

(3) Customization

The customization sub index is computed as the average specific transportation cost of the asset type.

Customization index I, t = Transport Cost i, t / Tctotal, t (2)

Where i is the commodity and t is the year.

For all goods, except electricity, the Average Transport Cost (TCi, t) is the real) deflated) transportation cost per 100-Ton-KM reported for rail (Railway Board, 2024) and reported for road (Ministry of commerce, 2024) separately and is given as;

Average Transport Cost, ACi,t = Average {Road Freight Transport, TC, ROAD, t,t + Rail Freight Transport, TC, RAIL,T}/ GDP deflator,di, t (3)

TC_{total}, t = ∑ Tci, t where TC Total is the sum total of the average transportation cost.

Where, the GDP deflators are used to convert nominal rupees costs to real rupees costs.

For electricity as a commodity, which involves transmission rather than transportation. We use average network charges of the commodity electricity (per average actual consumption in units of KwH) reported from the annual energy audit reports (CEA, 2023). For the sake of consistency and accuracy, we use the following formulae for electricity transmission charges;

Transport Cost electricity, TC i,t = NWC I, T (network charges, INR/unit) x AC (Average Consumption IN Units)

Where network charges (INR /unit) are the tariff charges approved by the GRIDCO for the utility, and the average consumption (in units KwH) are reported by the distribution during annual load audit of a sample of High Tension consumers (100 KVA, HT). The network charges are different from wheeling charges applicable for cross utility energy transfers.

Model of Losses

We specify a regression model to the error types, sale value and disbursed claims to the IBBI resolved dataset as below;

$VLoss_{it} = \alpha + \beta_1 Ratio_i + \gamma_1 Si + \delta_1 Claim, i + \varepsilon i$ (3)

$Dist.\ Loss_{it} = \alpha + \beta_1 Ratio_i + \gamma_1 Si + \beta_1 LI + \delta_1 Claimi + \varepsilon$ (4)

Where,

LI = Log of Liquidation Value,

Si = Log of Sale Proceeds Amount

DI = Log of Distributed AMOUNT to Stakeholders

Claim= Log of Amount of Admitted Claims

VLoss, i = Si (Sale Proceeds Amount) - LI (Liquidation Value)

Dist. Loss, i = DI (Distributed AMOUNT to Stakeholders) – Claim, i (Amount of Admitted Claims)

The full sample is split into Defunct (Yes) and Defunct (No) Firms and two separate pooled regression models are fitted.

We proceed with the description of major variables in our framework in figure 1.

Major Variables

variables	Description
DEFUNCT INDICATOR	defunct or non-defunct firms
DISTRIBUTED	Distributed AMOUNT to Stakeholders
LIQUID	Liquidation Value,
SALE	Sale Proceeds Amount
Claim	Amount of Admitted Claims.
sale proceeds/liquidation value	Ratio of the sale value to liquidation value
Value Loss	difference in sale amount and liquidation Value
Claim Loss	difference in admitted claims amount and disbursed to stakeholders
sale/admitted claims	Ratio of the sale value to admitted claims
durability	durability rate
standardization	standardization rate
re-deploy ability	Asset re-deploy ability rate
asset specificity	asset specificity rate
Specificity	index
Industry	3 DIGIT INDUSTRY CODE
WPI	wholesale price
I-O Coefficients	Input-Output Transactions Coefficients (Output/Input)
	Source: Author's review from IBBI newsletter 2025.

When the claims are adjudicated and admitted in full, they must be distributed to all genuine stakeholders in complete and in full. In the resolution process, the value loss is the difference in sale amount and liquidation value, and is of utmost interest to all stakeholders few of the errors, such as the claim error, which is the difference between the admitted claims amount and the amount disbursed to stakeholders, are relevant to understanding the efficiency of the IBC process.

DATA:

The sources of data include insolvency registry (IBBI) and bureau of industrial statistics (MOSPI). The period of review includes historical reports as of 31st March 2025. The quarterly news bulletins of IBBI (2025) provide the periodic progress on the admitted, liquidated, sold, and disbursed amount for admitted and resolved firms. The two-part analysis proceeds with the sample dataset of resolved firms and the preparation of input-output share matrix. We

pulled a dataset of over 359 firms from IBBI news bulletin for recent years (2025, 2024) which comprised about 280 defunct and 79 non-defunct firms. The Firms are split as tags of Defunct (Yes or No) Firms.

Table 1 shows the Descriptive Statistics of the IBBI dataset (Figures in INR Millions)

Table 1: Descriptive Statistics

(Figures in INR Crores)

Sample	defunct	0.0	N= 79.0		defunct	1.0	N =280		Full Sample	N= 359.0		
Variables	Min.	Max.	Mean	Std. Dev.				Std. Dev.	Min.	Max.	Mean	Std. Dev.
ratio Admitted Claims	0.0	3.3	0.3	0.4	0.0	3.3	0.1	0.3	0.0	3.3	0.2	0.3
Sale Proceeds	0.0	3.7	0.4	0.6	0.0	3.5	0.2	0.3	0.0	3.7	0.2	0.4
ratio Distributed to Stakeholders	0.0	1.9	0.4	0.4	0.0	51.0	0.5	3.9	0.0	51.0	0.5	3.4
Amount of Admitted Claims	0.1	4.4	1.8	0.9	-2.0	4.0	1.3	1.1	-2.0	4.4	1.4	1.1
Liquidation Value	-1.5	3.8	1.0	1.0	-2.0	2.8	0.2	1.0	-2.0	3.8	0.4	1.0
Sale Proceeds	-1.5	4.0	1.2	1.0	-2.0	2.8	0.3	1.0	-2.0	4.0	0.5	1.1

Amount Distributed to Stakeholders	-2.0	4.5	1.2	1.0	-2.0	2.8	0.3	0.8	-2.0	4.5	0.5	1.0
value loss= sale-liquid	0.0	0.6	0.16	0.1	-2.0	2.0	0.04	0.3	-2.0	2.0	0.1	0.3
distributed loss (=claim admitted-disbursed amount	-0.3	2.6	0.63	0.5	-2.0	4.3	0.97	1.0	-2.0	4.3	0.9	0.9
distributed loss =liquid value-disbursed	0.0	0.6	0.16	0.1	-2.0	2.0	0.04	0.3	-2.0	2.0	0.1	0.3
distributed loss (= claim Admitted-liquidation)	-0.5	2.4	0.81	0.5	-2.0	4.7	1.04	1.0	-2.0	4.7	1.0	0.9

source : authors calculation from IBBI dataset, 2025

Between the Defunct and Non-defunct firms it is observed that the mean value loss (INR 1.6 Million) is higher for Non-defunct firms than defunct firms (INR 0.4 Million). The mean sale amounts are lower (INR 4.0 mm) for Non-defunct firms than defunct firms (INR 35.0 mm). Similarly, the mean distributed loss is lower (INR 6.3mm) for Non-defunct firms than defunct firms (INR 9.7). Further, the mean value-distributed loss for liquidate to disbursed is lower (INR 1.6mm) for defunct firms than the non-defunct firms (INR 0.4mm), and the mean distributed loss for admitted to liquidation) for Non-defunct firms is lower (INR 8.1MM) than defunct firms (INR 10.4MM). This shows the efficacy and IBC resolution process efficiency in India. Since the differences between defunct and non-defunct firms are higher, this implies the gains in going concern firms vis-a-vis liquidated firms. The stakeholders' claims recovery are settled at a higher rate than liquidated firms.

RESULTS:

In the first part, we proceed with measuring the changes to the final output value of goods that can be generated from

the input vector of WPI and the matrix of input-output technology co-efficient for all sectors. We multiply the prices vector with the I-O coefficients to generate the sectoral values and the related market shares. The WPI vectors (12x1) are mapped against the matrix (12x12) I-O for all three years, 2007-08, 2015-16, and 2024-25. Since we can compare only real values, we derive the real expenditure data by normalizing with GDP deflators for both 2007-08 and 2015-16 to arrive at the real expenditure I-O matrix (12 x12). Later, similarly, for projecting the real input and output values for 2024-25 we use the GDP deflators.

The difference tests are conducted for the real aggregate input and output values between 2007-08 and 2015-16 and the projected real aggregate input and output values for the year 2024-25.

Table 2 shows the Chi-Square Tests of the Difference between sectoral Input and Output Values (2007-08, 2015-16).

Table 2: Chi-Square Tests of the Difference between the Input and Output Values (2007-18, 2015-16)

Real Aggregate Measure	Min.	Max.	Mean	Std. Dev.	Chi-Square (P-Value)	Likelihood Ratio Tests (P-Value)
Input 2007	0.0	36.9	9.658	11.28		
Output 2007	0.0	24.3	6.37	7.43		
Input 2016	0.0	11.7	4.22	4.39		
Output 2016	0.0	25.9	9.39	9.74		
Input 2025	0.0	14.0	5.08	5.27		
Output 2025	0.0	31.1	11.25	11.69		
(Δ) Input 2016 Change Over Input 2007	-25.1	4.9	-5.417	9.77	120.0 (0.24)	56.8 (0.99) df=110
(Δ) Input 2024 Change Over Input 2016	0.0	2.3	0.83	0.86	132.0 (0.23)	59.6 (0.99) df=121
(Δ) Output 2016 Change Over Output 2007	-13.6	16.6	3.01	8.74	96.0 (0.26)	50.2 (0.99) df=88
(Δ) Output 2024 Change Over Output 2016	0.0	5.1	1.85	1.92	84. (0.27)	45.7 (0.99) df=77
N =12	1. ( ) parenthesis shows Prob. Significance values					
Note	2. Chi-Square values are insignificant at 5%					
	4. Sectoral output values are adjusted for inflation using GDP deflators.					
Source	Author's calculation from compiled I-O and WPI dataset.					

The descriptive statistics show the changes to real sub-aggregate values of input and output over the years. Consistently, the mean of the changes for both the aggregate measures are positive for 2016 (4.9 & 2.3) and for 2024 (5.1 & 6.6). We infer from Table 2 that the mapping between the periods of 2007-08, 2015-16 and 2024-25 are

consistent. Since there is no shift in the values of I-O co-efficient, the I-O coefficients for all the three periods 2007-08, 2015-16 and 2024-25 are stable.

Next, we compute the Pearson correlation between the changes to the values of sectoral output and the changes to I-O values. Table 3 shows two sets of the Pearson correlations test between real aggregate input values for 2007-08, 2015-16 and 2024 and real aggregate output values for 2007-08, 2015-16 and 2024 separately. Since the chi-square tests for the (Δ), changes are insignificant; this implies that the re-usability of commodities for both the periods (2007) and 2016 have remained unchanged. The correlation test is a measure of the consistency and accuracy in the mapping of the twelve sectors (12) for all years in the dataset.

Table 3 shows the distribution of the three major components of the asset specificity index (ASI) for both the years 2023 and 2024.

Table 3: Distribution Of The Components Of The Asset Specify Index (2022-23, 2023-24)

Year	2022-23	2023-24	2022-23	2023-24	2022-23	2023-24		
Asset CATEGORY	Asi Geometric Mean = $\{(5) \times (7) \times (8)\}^{1/3}$	ASI Geometric Mean = $\{(6) \times (7) \times (8)\}^{1/3}$	ASI Simple Mean = 1/3 {(5) + (7) + (8)}	ASI Simple Mean = 1/3 {(6) + (7) + (8)}	CUSTOM (C)	CUSTOM (C)	Re-Deploy Ability (R)	Durability (D)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Construction	0.058	0.046	23.80	23.79	0.01	0.01	22.89	0.90
DURABLE SERVICES	0.001	0.000	0.918	0.914	0.01	0.01	0.31	0.60
Electricity	0.001	0.001	3.841	3.841	0.00	0.00	3.24	0.60
FOOD	0.001	0.001	1.838	1.838	0.01	0.00	0.84	0.99
FUEL	0.000	0.000	0.878	0.867	0.03	0.02	0.00	0.85
MANUFACTURED	4.569	2.198	32.39	32.01	0.74	0.35	31.06	0.60
MANUFACTURED FOOD	0.000	0.000	0.632	0.618	0.03	0.02	0.00	0.60
Mineral	0.022	0.019	22.41	22.41	0.01	0.00	21.81	0.60
Non-Food	0.375	0.354	13.83	13.82	0.14	0.14	13.09	0.60
SERVICES	0.053	0.050	21.35	21.35	0.01	0.01	20.74	0.60
TEXTILE	0.000	0.003	0.642	0.969	0.00	0.33	0.04	0.60
TRANSPORT	0.016	0.488	21.78	21.87	0.00	0.10	21.08	0.70
note	FOOD, Fuel, Durable Services and Manufactured Food have the minimum ASI values.							

Source	author's calculation from I-O transaction Table, MOSPI, Finance Bill, 202, dgcis Movement of Goods inland Roads and Annual Accounts of Railway BOARD, 2024

Table 4 shows the Pearson Correlation (ρ) between the changes to WPI and sector output values.

Table 4: Pearson Correlation (ρ) between the changes to WPI and sector output values from I-O Table (2007-08, 2015-16 and 2024-25)						
Real Aggregate Measure	Input 2007	Output 2007	Input 2016	Output 2016	Input 2025	Output 2025
	ρ (t-value)					
Input 2007	1 (0.00)	1 (0.08)	0.51 (0.00)	0.51 (0.00)	0.51 (0.0)	
Output 2007	1 (0.00)	1 (0.08)	0.51 (0.00)	0.509 (0.00)	0.509 (0.00)	
Input 2016	0.5 (0.08)	0.5 (0.08)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)
Output 2016	0.5 (0.09)	0.5 (0.09)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)
Input 2025	0.5 (0.09)	0.5 (0.09)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)
Note	1. ( ) parenthesis shows 2 tailed significance prob. values 2. * shows prob. values are significant at 10% 4. Sectoral output values are adjusted for inflation using GDP deflators.					
Source	Author's calculation from compiled I-O and WPI dataset.					

Table 4 shows that the correlation tests are significant.

In the next part, the full sample is split into Defunct (Yes) and Defunct (No) Firms and pooled regression model is fitted.

Table 5 shows the regression model for distributed loss for split samples (Defunct/Non T defunct) and the full sample of resolved firms in the IBBI dataset.

Table 5:	Distributed Loss Model				
Dependent Variable	Distributed loss (= Claim Admitted - Distributed Amount Stakeholders) $Dloss_{it} = \alpha + \beta_1 ASI_i + \beta_2 Ratio_i + \gamma_1 Si + \beta_1 LI + \delta_1 Claimi + \varepsilon$ (1)				
SAMPLE	DEFUNCT INDICATOR = YES (N= 287)	DEFUNCT = NO (N=79)	FULL SAMPLE (N =359)		
Model Variable	Beta (t-Values)				VIF
Constant	-0.033(-0.452)	0.434(2.456)	0.101(1.586)		

Asi index 2023-24 geometric mean*	0.133(3.345)	0.032(0.728)	0.063(1.993)		1.45
Amount of Admitted Claims*	0.843(19.745)	0.453(3.338)	0.74(19.459)		1.52
ratio Sale Proceeds	-0.167(-1.384)	-0.152(-1.41)	-0.202(-2.547)		1.104
Ratio liquid to sale	0.016(0.76)	-0.076(-1.31)	-0.009(-0.478)		
Sale Proceeds	-0.479(-10.201)	-0.438(-3.619)	-0.523(-13.415)		
ratio Distributed to Stakeholders*	-	-	-0.048(-5.32)		
R^2	0.603	0.345	0.557		
R^2 Adjusted	0.599	0.319	0.553		
SSE	154.33	6.881	157.375		
MSE	51.443	2.294	52.458		
Note	1. ( ) t-Values > 1.632 denotes significance at 10% 2. * denotes significance at 10% Probability 3. VIF < 2.0 implies the absence of multi-collinearity in the model. 5. R2= 0.40 implies a moderate fit model.				
Source	Authors estimation from compiled dataset				

The claim distribution loss model finds three significant variables, Asset specific index 2023-24 geometric mean, Amount of Admitted Claims, ratio Distributed to Stakeholders, respectively.

Table 6 shows the regression model for value loss for split samples (Defunct/Non T defunct) and the full sample of resolved firms in the IBBI dataset.

Table 6 :	value loss Model

Dependent Variable	Value loss (= Sale- Liquidation) $Vloss_{it} = \alpha + \beta_1 ASI_i + \beta_2 Ratio_i + \gamma_1 Si + \delta_1 Claimi + \varepsilon i$ (2)			
	DEFUNCT INDICATOR = YES (N= 287)	DEFUNCT indicator = NO (N=79)	FULL SAMPLE (N =359)	
Model Variable	Beta (t-Values)			VIF
Constant	-0.036(-0.945)	0.036(1.034)	-0.132(-3.686)	
ASI 2023-24 simple mean*			0.002(1.566)	1.02
ASI 2023-24 gEOMETRIC mean	0.015(0.643)	-0.024(-2.073)		
Amount of Admitted Claims*	0.024(1.175)	0.05(3.648)	0.109(5.676)	1.75
ratio Sale Proceeds	0.113(1.729)	0.034(1.721)	0.174(4.319)	1.18
Ratio liquid to sale*	0.039(3.195)	0.037(2.424)	0.045(4.598)	1.09
Liquidation Value*			-0.125(-6.306)	1.85
R^2	0.235	0.135	0.119	
R^2 Adjusted	0.205	0.125	0.112	
SSE	0.288	4.603	4.34	
MSE	0.096	1.534	1.447	
Note	1. ( ) t-Values > 1.632 denotes significance at 10% 2. * denotes significance at 10% Probability 3. VIF < 2.0 implies the absence of multi-collinearity in the model. 5. R2= 0.40 implies a moderate fit model.			
Source	Authors estimation from compiled dataset			

The value loss model finds three significant variables, ASI 2023-24 gEOMETRIC mean, Amount of Admitted Claims,

Ratio liquid to sale, and Liquidation Value, respectively. For all the three sample groups in Table 5 and Table 6, we find three variables; Amount of Admitted Claims, Sale Proceeds and Ratio (sale /liquid) are significant in the model. This implies that the efficiency of the IBC resolution is significantly impacted by the sale proceeds amount, which is negative and significant. The sales to liquid value ratio is positive and significant which implies the liquidation value is positively related to the disbursal amount (Distribution = Admitted – Disbursed). Similarly, for all the three models in equation (1-3) in Table 5 and Table 6, we find the amount of Admitted Claims, Liquidation Value, and Sale Proceeds are significant in the model. This implies that the re-sale value losses are significantly attributed to the Amount of Admitted Claims, Sale Proceeds in the dataset. Since the value loss is positively impacted by the admitted claims, it shows that higher volume of claims would signify the intangible value of the firm vis-a-vis the tangible value.

The wholesale prices (WPI) of assets positively impacts firm market value cannot be rejected because the annual average WPI (new series 2011-12) of all commodities shows significant correlation with the final value of output in the dataset.

Robustness

The robustness tests involve a chi-square test of the type1 and type 2 errors based on a contingent table between the new tag and old tags. The method of creating new tags is based on a threshold value of the estimated errors from the Dloss model (1).

We calculate the Vloss model errors as;

$$Dloss\text{-}error^{\wedge} = Distributedloss - Distributedloss^{\wedge} \qquad (5)$$

Where Dlosserror$^{\wedge}$ is the estimated error from Dloss Model (1)

Distributedloss is the observed distributed loss from the dataset,

Distributedloss$^{\wedge}$ is the estimated distributed loss from Dloss Model (1).

Since the $Dlosserror^{\wedge}$ represents a magnitude (score), we use the score's cut-off points (thresholds) to create a new tag (defunct/non-defunct). For simplicity we define positive errors ($Dlosserror^{\wedge} > 0$) as defunct firms and negative or zero errors ($Dlosserror^{\wedge} =< 0$) as non-defunct firms.

The selection of these thresholds is based on the ex-ante observation of the old tag and any tampering of the cut-off score could lead to revised predicted outcome (Liquidation or Sale amount, claims admitted or distributed amount).

A cross tabulation report (swap set) of the overlap between the previous defunct tag and the new tag is created. Subsequently, the distribution profiles of newly tagged firms against the bau (business as usual tags).

The classification table (fitness matrix) shows that the regression models (1-2) accurately tag more than 70% (type I error) and 65% (type II error) of all firms in the sample.

As mentioned, the cut-off scores (efficiency scores) from the first run of models (1 -2) are used to reclassify (retag) the original sample (359) into revised tags (defunct/non-defunct) by using a simple rule of estimated error cut off from the estimates of models (1-2). A cross tabulation report (swap set) of the overlap between the previous defunct tag and the new tag is created.

Table 7 shows the results of the revised sample (359), residual errors are lower, and value loss (liquidation value, re-sale value, disbursal values) are lower.

Table 7 also shows the cross-tabulated view of the old tag and new tag in the full sample dataset. Swap set analysis of the new tag.

Table 7: Distribution of Reclassification errors using Dloss Model (1)				
Old tag x New tag	Count	Average of Vloss Errors (sale-liquid)	Average of Dloss Errors (claim-disbursed)	Difference in value loss errors Average of Vloss Errors (sale-liquid)
00	54	0.18	0.53	-0.11
01	25	0.13	0.84	-0.02
10	120	0.08	0.39	-0.21
11	160	0.01	1.40	-0.14
Total	359			
old	Count	Average of Vloss Errors (sale-liquid)	Average of Dloss Errors (claim-disbursed)	
No	280	0.16	0.63	
Yes	79	0.04	0.97	
Total	359			
Summary				
	NEW DEFUNCT STATUS			
DEFUNCT STATUS	yes	NO	total	
YES	160	120	280	
NO	54	25	79	
	214	145	359	
McNemar chi-squared test on 1 degree of freedom= (b12-a21)^2/(b12+a21)	25.03			
Note	McNemar chi-squared test shows a significant difference between the two proportions The Average of Vloss Errors (sale-liquid) has reduced in the new classification tags.			
Note				
source	Authors calculation			

Table 7 shows reduction in sale loss errors when non-defunct is tagged as defunct using Model (2), and non-defunct are tagged as defunct using model (2). Hence, there is overall reduction in the value losses.

The sale to liquid errors are lower. The claim to distributed errors are lower

The results of the hypothesis tests are described hereafter. The first hypothesis H1 that a well-developed buyer's market is essential to the resale value of "specific" assets, cannot be rejected because matured markets correspond to more numbers of buyers and sellers.

Table 7 shows the robustness tests and comparative performance of the new tag against the old tag, the improvement in parameters (sale proceeds, distributed amount) and reduction in losses (value loss, claim loss). The proportion

(76%) of false defunct tag (Type II, 25/79) and the proportion (55%) (False non-defunct tag (Type I, 160/280) confirms the extent of mis-classification. The hypothesis H2 cannot be rejected.

Table 5 and Table 6 show the distinction between both the models fitted in equation (3) and (4). The errors in firm value of non-defunct firms that are distinct from defunct or liquidated firms cannot be rejected because this shows that the constructed ASI index could reduce the mis-classification error.

The third hypothesis H3 of the Fair valuation is positively related to asset specificity and cannot be rejected. The Average of Vloss Errors (sale-liquid) and Average of Dloss Errors (claim-disbursed) for the overlap cells (between new-old tags) are lower. Hence, hypothesis H2 cannot be rejected.

We generated Asset Specific Index (ASI) using three important sub-indices and provided comparison of the indices by two standard formulas in the literature (Fisher, 1976), both the simple mean and the geometric mean. Table 7 shows the descriptive of The distribution of the ASI index computed shows the sectors which have low deploy ability, durability and high custom (e.g. stationery off road construction equipment) vis-à-vis high deployability, high durable and low custom assets (e.g., Transport). Our findings are validated with previous results (James et al., 2014) that identified groups of low mobility, low durables, and high custom assets. These findings directly address the question of asymmetric information on the subjects.

Therefore, the summary of hypotheses tests are given as; H1: secondary market is essential for eventual successful resolution; H2: there exist definite misclassification errors in outcome; H3: Fair value is related to asset specificity, and H4: Asset Specificity Index improves the resolution efficiency of bankrupt firms. respectively.

Discussions:

The regression model results explained the contribution of the significant parameters that contributed to the error and the resolution efficiency. Since the Claim errors, the difference in admitted claims amount and disbursed to stakeholders, are relevant to evaluate the efficiency of the IBC process.

Specifically, our analysis established the disbursal shortfalls to ASI, liquidation Value, Sale Proceeds and the Amount of Admitted Claims. We found that in going concern firms, the stakeholders' claims are settled at a higher rate than liquidated firms. When the claims are adjudicated and admitted in full it must be remitted (in full) to genuine stakeholders post the liquidation. These findings are in conjunction with previous results suggested by Pulvino (1998) and Weiss (1990), fair value losses in the range of 30% to 50%, for assets with high specificity during bankruptcy.

Our findings are in line with Cambells' (1996) where the re-payment to the secured creditor is higher than the defunct re-sale amount.

Restructuring may not be possible when the firm's value under restructuring is higher than a bankruptcy sale. Post facto resolution favors larger size firms profitable. Since insolvency is costly, the tradeoff between the loss aversion and aversion leads to optimal equilibrium outcome.

The creditors know that the small firm's existing value is more than its bankruptcy sale. Based on the model, we determine the additional conditions required for a successful. This focuses on the choice of methods adopted by creditors. We discuss the implications of our findings to the benefits of creditors.

The registered valuators and practitioners who may consider each entity in its life cycle as unique and may be treated differently from others. Economic models provide a practical screening mechanism in IBC. Since the situation for defunct firms is different from non-defunct (active) firms, practitioners must view both the categories separately. The

foreclosures could be a more attractive mechanism for creditors than the legal process. We suggest that an inefficient insolvency framework may lead to a higher prevalence of defunct firms.

Conclusions

In this paper, we developed a specificity index and explained the variations in asset quality relevant for resolution. We highlighted the major causes contributing to the differences along with their limitations and caveats. We found that assets used in different industries have variations in asset specificity. The study uses a sample of 359 unlisted firms that filed bankruptcy in 2024 and obtained a resolution (functional or liquidation) by the end of 2025.

There are many demand-driven factors such as the inflation that may affect the re-sale prices of assets, shifts in the technology (e.g., I-O coefficients); import intensity of input commodities, transition towards renewables, etc. could cause an impact in firm value. Similarly, supply driven or macro-economic factors, such as wholesale prices (WPI), exchange rate, and the cost of refinance rates, and real wages are important. The status of the evolving regulatory landscape also plays an important role in terms of associated transaction and compliance costs on the industry, viz; certification, accreditation, licensing, approval, amended land laws, direct or indirect tax rules, etc. methodical disputes can lead to poor realization and low recovery.

However, any improvement in the ease of doing business (World Bank's ease index, 2022) could go a long way in improving the realized value of re-sale assets. There are few limitations in our study, the availability of resolved dataset of firms with asset wise time series. Further, since the characteristics of assets would vary widely, the RVs and practitioners will not find a single field application framework. Overall, the findings the inaccuracies in the insolvency resolution practices. These findings can provide useful information for modeling analyses, and for testing and uncovering errors in valuation. Further research may reduce the information asymmetry between the firm and all stakeholders

Declaration:

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Confict of interest	The author has no conflict of interests

List of Abbreviations:

IBBI insolvency and bankruptcy board of India

IBC insolvency and bankruptcy code

RV registered valuators

WPI wholesale prices

CIRP corporate insolvency and resolution professional

RLOSS realized loss - sale value

Loss Liquidated firm value - Sale value

DLOSS distributed loss = total admitted claims - total realized re-sale value

Haircut (loss) = total admitted claims - net distributed amount.

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APPENDIX

Table A1 : Input Output Classified Table For The Year 2007-08 For 12 Sectors (Figures In Inr 10 Millions)

Prices	Category	Construction	Durable Services	Electricity	Food	Fuel	Manufactured	Manufactured Food	Mineral	Non-Food	Services	Textiles	Transport
	Total Input	3728461.5	3410 6087.2	########	1114 5891.4	########	########	########	351857.1	########	676589.1	546498.2	194944.9
Wpi	Total Output	5649320.0	6004 8761.0	########	1927 7836.1	########	########	########	########	########	########	1092750.2	277829.3
115.90	Construction	121069.1	396149.9	280003.7	164518.0	157857.7	154774.4	45237.7	3520.0	74372.7	124215.4	28149.2	437.2
114.95	Durable Services	290811.5	191 3164.5	415700.1	285933.3	168819.2	175414.3	278098.7	24431.0	392325.1	211662.2	50284.9	12166.8

105.30	Electricity	247557.4	263882.3	##########	454102.0	159334.5	208991.1	586728.8	267222.8	93495.5	31505.5	30168.5	5269.6
111.03	Food	152.1	1190863.1	191611.1	7436060.2	0.0	139223.3	503445.5	0.0	23323.3	116.1	59731.7	22.3
120.92	Fuel	664192.4	0.0	##########	17.7	105120.6	90305.5	130957.7	17993.3	0.1	411.5	970.4	27.3
114.92	Manufactured	1185641.5	1800441.4	##########	1336665.5	568569.6	765593.1	357534.1	189636.9	385198.5	59197.9	54833.0	134835.1
110.31	Manufactured Food	3605.2	2804.7	5847.0	40903.6	0.0	873.1	39821.7	0.0	0.0	121.7	1086.0	1.7
122.50	Mineral	340162.5	0.0	7396.9	3.1	0.0	37547.7	1.4	0.0	0.3	0.0	0.0	80.6
102.29	Non-Food	12.4	0.0	6675.5	1420.9	0.0	763614.8	631.9	0.0	91888.6	0.0	0.9	1083.0
113.93	Services	669514.3	1107539 6.6	##########	1195225.0	329059.3	581681.3	153663.3	94480.8	375235.3	244346.8	145186.1	36886.7
100.80	Textiles	18782.9	93163.0	37328.5	86642.4	3600.4	68695.5	2080.1	3066.1	55399.5	14615.6	19245.7	392.6
104.97	Transport	186960.3	330721.8	273426.8	144399.8	68995.4	55514.5	36550.4	8200.2	19509.4	35505.5	89768.2	3742.1

Source : Author's Compilation From Input-Output Transactions Table And Bureau Of Industry, 2024

Table A2 : Input Output Classified Table For The Year 2015-16 For 12 Sectors (Figures In Inr 10 Millions)

Prices (Wpi)	Category	Construction	Durable Services	Electricity	Food	Fuel	Manufactured	Manufactured Food	Mineral	Non-Food	Services	Textiles	Transport
	Total Input	3804898	843160	4011740	3492546	5501580	4015302	3624870	83229	801302	792653	314576	1241108
	Total Output	8424162	1505800	6835732	1459 3870	1459 8569	7367546	4216 2875	226700	153737 00	110071 22	191327 3	2451505

112.8	Construction	644710	6244	2854742	157310	4213	1106	10304	34	0	270432	120	5060
105.0	Durable Services	86644	45584	2814998	1957	174	3990	7876	136	0	484670	203	12209
103.7	Electricity	91236	103865	476567	635818	131413	17246	28059	1072	0	426663	13150	88630
139.7	Food	23754	0	999478	806806	0	876391	2168 4709	0	634455	702676	39764	2457
82.2	Fuel	0	0	47320	0	475	0	0	0	0	0	0	0
106.9	Manufactured	874659	281221	1370 2561	566430	2519397	2761022	1414993	36689	125396	1421295	46987	853112
122.5	Manufactured Food	3	0	24652	0	0	0	2443195	0	9525	17	3	0
111.0	Mineral	614281	0	12045	0	283461	2242	359286	0	561464	0	0	11
112.3	Non-Food	368726	0	3478248	0	0	9789	1671104	47	289311	410510	4736	24
113.0	Services	584132	274830	1293 2802	915647	162176	248307	666279	16281	345913	2384040	65666	220076
111.3	Textiles	1121	45509	197936	503	2067	25967	6490	6211	4158	1095	116079	1272
117.5	Transport	593612	821770	2557 130	408072	938442	692400	1953 055	22630	248748	182433	27867	57649

Source : Author’s Compilation From Input-Output Transactions Table And Bureau Of Industry, 2024