

CSEP Working Paper-52
July 2023

Centre for
Social and
Economic
Progress

CSEP

Independence | Integrity | Impact

₹

**COMMODITY PRICES
AND THE TWIN BALANCE SHEET**

CRISIS



ABHISHEK KUMAR AND DIVYA SRINIVASAN

Copyright © Abhishek Kumar and Divya Srinivasan

Centre for Social and Economic Progress (CSEP)
CSEP Research Foundation
6, Dr Jose P. Rizal Marg, Chanakyapuri,
New Delhi - 110021, India

Recommended citation:

Kumar, A., Srinivasan, D., (2023). *Commodity Prices and the Twin Balance Sheet Crisis* (CSEP Working Paper 52).
New Delhi: Centre for Social and Economic Progress.

The Centre for Social and Economic Progress (CSEP) conducts in-depth, policy-relevant research and provides evidence-based recommendations to the challenges facing India and the world. It draws on the expertise of its researchers, extensive interactions with policymakers as well as convening power to enhance the impact of research. CSEP is based in New Delhi and registered as a company limited by shares and not for profit, under Section 8 of the Companies Act, 1956.

All content reflects the individual views of the authors. The Centre for Social and Economic Progress (CSEP) does not hold an institutional view on any subject.

CSEP working papers are circulated for discussion and comment purposes. The views expressed herein are those of the author(s). All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including copyright notice, is given to the source.

Designed by Mukesh Rawat

Commodity Prices and the Twin Balance Sheet Crisis

Abhishek Kumar*

Non-Resident Associate Fellow
Centre for Social and Economic Progress
New Delhi, India
Assistant Professor (Lecturer),
University of Southampton

Divya Srinivasan**

Research Associate
Centre for Social and Economic Progress
New Delhi, India

The authors are grateful to Rakesh Mohan for his guidance and useful comments. They would also like to thank Shishir Gupta, Chetan Ghate, Sajjid Chinoy, Abhiman Das, Janak Raj, Rajesh Chadha, and Laveesh Bhandari for their useful comments on an earlier version of this paper.

*E-mail: AKumar@csep.org, **E-mail: DSrinivasan@csep.org

Table of Contents

Abstract	6
1. Introduction	7
2. Data	11
3. Exposure to the Iron and Steel Industry and Non-Performing Assets	12
3.1 Research Design	12
3.2 Results	13
Baseline	13
Assets Quality Review and Non-Performing Assets: Measurement Issue	15
Lending Boom and Non-Performing Assets	16
Falsification Test	17
Placebo	18
3.3 Quantifying the Effects of Exposure to the Metal Sector	19
3.4 Alternative Identification Using a Forward-Looking Variable	21
4. Price Shock, Profitability and Defaults	24
5. Concluding Remarks and Policy Implications	30
References	33
Appendix	35

List of Figures

Figure 1: Gross Non-Performing Assets across Bank and Bank Groups	8
Figure 2: Slippage and the Metal Price Index	9
Figure 3: Incremental Slippage for Exposed and Non-Exposed Banks	14
Figure 4: Incremental Slippage for Exposed Banks (Pre-AQR)	15
Figure 5: Incremental Growth in Advances for Exposed Banks	16
Figure 6: Validity of Treatment (Falsification Test)	17
Figure 7: Wholesale Price Index (Actual and Projected) For Metal and Drugs and Pharmaceuticals.	18
Figure 8: Incremental Slippage and Growth in Advances By Banks Exposed to the Drugs and Pharmaceuticals Industry	19
Figure 9: Event Study on Evolution of Slippage in Exposed versus Non-Exposed Banks	21
Figure 10: Event Study (Slippage and Slippage+Restructured)	22
Figure 11: Event Study (Slippage and Slippage+Restructured)- with bank-level controls.	23
Figure 12: Some Indian Metal Price Indices and Exchange Rates	24
Figure 13: Prices and Profitability (Metals and Drugs & Pharmaceuticals)	26
Figure 14: Profits, Borrowings, and Investments	27
Figure 15: Share of Credit to the Metal Sector and Sectoral NPAs	28
Figure 16: Profits and Cash Flow from Borrowings Of Defaulted versus Other Firms	29
Figure 17: Defaulted versus Other Firms (Labour and Material Share)	30
Figure A.1: Incremental Slippage of Banks exposed to Iron and Steel Sector (2005-2018)	35
Figure A.2: Incremental Slippage of Banks exposed to Iron and Steel Sector (2005-2020)	36
Figure A.3: Incremental Growth in Advances of Banks exposed to Iron and Steel Sector (2005-2018)	36
Figure A.4: Incremental Growth in Advances of Banks exposed to Iron and Steel Sector (2005-2020)	37
Figure A.5: Incremental Slippage of Banks exposed to Metal Sector (Iron & Steel and Metal Products) ...	37
Figure A.6: Incremental Growth in Advances of Banks exposed to Metal Sector	38
Figure B.1: Event Study Analysis: Evolution of Slippage and Slippage+Restructured	38
Figure B.2: Event Study Analysis: Evolution of Slippage and Slippage+Restructured (with Bank-level controls). 39	

Figure B.3: Event Study Analysis: Growth of Advances	40
Figure C.1: Average unit price of imports (of iron and steel and articles of iron and steel) from China and the rest of the world excluding China	41
Figure D.1: Cash flow from borrowing by firms in the metals industry	43
Figure D.2: Cash flow from borrowings by firms in the drugs and pharmaceutical industry	43
Figure: E.1: Profitability ratios of defaulting firms relative to all others.	46
Figure: E.2 Share of Defaulted firms in Sales and Total Assets	46
Figure F.1: Return on Assets and Equity across Bank Groups.	47
Figure F.2: Evidence from the Stock Market.	47
Figure: G.1: Sectoral lending across Bank Groups.	48
Figure H.1 Average Treatment Effect (ATT) on Banks Exposed to Iron & Steel Sector	51

List of Tables

Table: 1 Slippage, Growth of Advances and Exposure to the Iron and Steel Industry in 2011	20
Table 2: Operating Profit to Sales and Commodity Prices in the Metal Industry.	26
Table 3: Operating Profit to Sales and Commodity Prices in the Drugs and Pharmaceuticals Industry. ...	27
Table: C.1 Exchange rate pass-through regression	42
Table: D.1 Cash flow from borrowing and financial productivity: Metals sector	45
Table: D.2 Cash flow from borrowing and financial productivity: Drugs and pharmaceutical industry ...	45
Table H.1: Gross NPAs (as a % of gross advances)	49
Table H.2: Exposure and gross NPAs of ICICI Bank (1999-2001)	50

Abstract

In the workhorse new Keynesian models, sectoral deflation is of little consequence unless it affects overall inflation. But in practice, sectoral deflation combined with nominal debt contracts and rigidity in the labour market can have large and significant adverse effects. Using data from India (the second-largest steel producer in the world), we estimate the effect of large movements in metal prices during 2011-16. As expected, a decrease in commodity prices led to a decline in profit in general, with defaulting firms experiencing an even larger decline in their profitability. Using a difference-in-differences design, we find that banks with higher exposure to the metal sector declared significantly higher non-performing assets after the commodity price crash, compared to banks with little or no exposure. Hence, a large decline in commodity prices can cause a prolonged twin balance-sheet crisis, an area that has not received enough attention in the existing literature. This type of balance-sheet crisis hurts credit and economic growth in the medium run. Results also suggest that the large decline in domestic metal prices post 2011 was mostly driven by lower prices of imports from China and the less-than-proportionate depreciation of India's nominal exchange rate.

Keywords: Metal Prices; Sectoral Exposure; Exchange Rate Pass-Through; Profitability; Non-performing Assets

JEL Classification: E31; G21; G23

1. Introduction

Banks help in transferring funds from savings-surplus units (depositors) to savings-deficit units (borrowers) and are important for financial intermediation. They incur risks in the normal course of business as borrowers may fail to fulfil their obligations, but depositors have to be paid back. In an accounting sense, deposits are liabilities and loans are assets for a bank. If the assets are not generating a return, either through interest or principal repayment or both, the bank classifies them as ‘non-performing’. According to the Reserve Bank of India (RBI), a ‘non-performing asset’ is defined as credit in respect of which interest and/or instalment of the principal has remained ‘past due’ for over 90 days. In this paper, we define non-performing assets (NPAs) as a proportion of gross advances to make the term comparable across banks and time.

The transition of NPAs in the Indian banking system has been tumultuous: they amounted to around 16% in scheduled commercial banks during the mid-1990s. This was a time when the financial sector was undergoing several reforms, including those aimed at enhancing the banking system’s health. These reforms combined with the momentum of India’s GDP growth resulted in a decline in NPAs¹ to a little over 2%² over the next several years; from 2011 onward they started rising.

Figure 1 depicts the overall as well as bank-group-wise (based on ownership) NPAs. In India, the NPAs were largely concentrated in public sector banks (PSBs), as can be seen by the gross NPA ratios across bank groups. Owing to this, governance issues in PSBs have often been cited as one of the main reasons for the accumulation of NPAs. But it is hard to believe that bank governance deteriorated so rapidly, given that PSB’s performance had been improving compared to private banks until the beginning of the North Atlantic financial crisis in 2008-09. Not only did PSBs improve their performance, but their NPA ratios were significantly lower than those of private banks from 2007-08 to 2010-11: PSB ratios were a low of 2% in 2008-09, while the ratio for private banks was 900 basis points higher at 2.9%. While bank management does change every few years, there was no discernible change in management incentive structures over this period. Therefore, it is unlikely that management practices would improve only for few years and then slide back. It is also not the case that private banks have negligible NPAs. If the stakeholder is held responsible for the difference in performance across banking groups, this rationale should equally apply to non-financial firms. However, we see that a large portion of the bad loans emanated from privately owned non-financial firms. Stronger evidence is consequently required to substantiate the premise of bad governance contributing to the massive build-up of NPAs which is missing.

In 2008-09 the RBI set in place forbearance measures to mitigate the impact of the North Atlantic financial crisis³. The *Economic Survey* (2020-21), an annual government publication, has argued that regulatory forbearance was extended beyond the period required and hence had adverse consequences⁴, and Chari et al. (2021) attribute the increase in NPAs to regulatory forbearance. They argue that forbearance over long periods may lead to the misallocation of credit due to the evergreening of stressed loans and lending to zombie firms. It is true that during the forbearance period, the volume of restructured loans increased, as did NPAs albeit with a lag, but Kumar et al. (2022) argue that evidence in support of zombie lending is very weak and it is hard to get any precise evidence. This is because lending decisions are based on a large amount of private information, and in the absence of such information even genuine lending can be construed as zombie lending by analysts. For example, the classification of firms as “zombie” by Chari et al. (2021) and the papers cited therein is based on observables from accounting statements, but we know that most project

¹ NPAs increased over 1997-2001, but mainly for new private sector banks.

² See Mohan and Ray (2017, 2019) and Mohan and Ray (2022) for a discussion of the Indian financial system and NPAs, respectively.

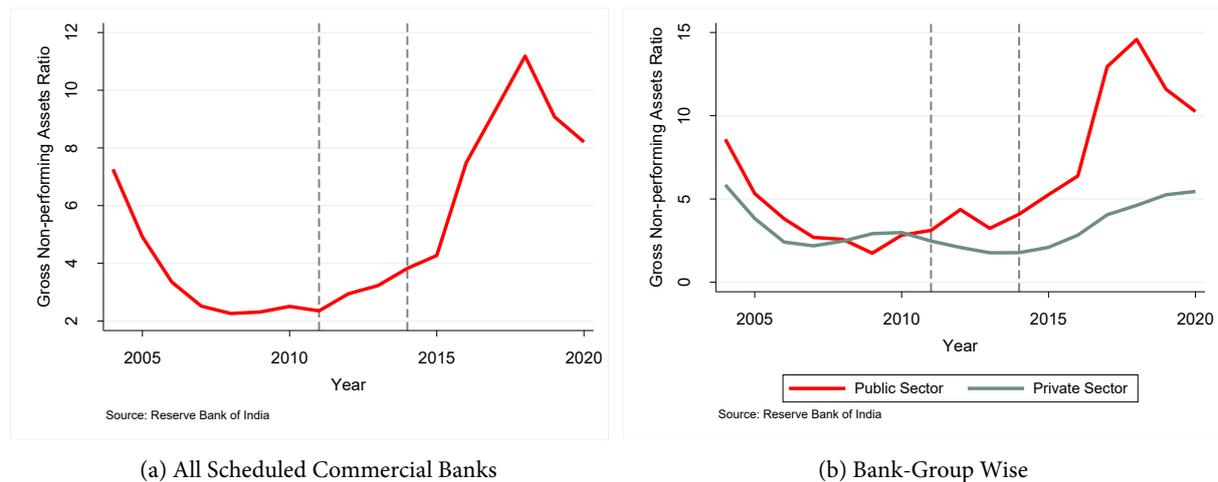
³ During the North Atlantic financial crisis in 2008-09, the RBI introduced regulatory forbearance. This policy allowed banks to reclassify their NPAs in order to save banks from higher provisioning, which would have affected credit growth and financial stability adversely during the crisis.

⁴ *Economic Survey 2021-22*.

loans are given for future expansion based on project proposals which may have very different information compared to observables in accounting statements.

These simple narratives around bad governance and zombie lending without credible evidence have stymied systematic efforts to explore the reasons behind the increase in NPAs and this paper aims to fill the gap. Moreover, there were two episodes of a sharp decline in commodity prices across this period during which NPAs increased. The first was during 2008-09 and the second was more prolonged, from 2011 to 2016. Despite a large amount of literature on NPAs and banking crisis (see Eberhardt and Presbitero, 2021, and papers cited therein), this channel has been completely ignored in the existing literature. Kumar et al. (2022) fills this gap, showing how NPAs in Indian banking and profit ratios in commodity-sensitive non-financial sectors are highly correlated with global commodity prices. The paper models commodity price shock as an income shock to banks, and show how a negative shock dents bank balance sheets which are exposed to sectors experiencing large decline in prices. Data from the newly instituted Insolvency and Bankruptcy Board of India (IBBI) indicate that Indian firms defaulted on debts above Rs 4 trillion between 2017 and 2020. More than half of all the claims filed by financial companies for recovery were brought against companies in the metal industry. Therefore, in this paper, using the data on bank lending to the metals sector and the metal price index, we explore the role of the fall in metal prices during the 2010s in creating NPAs in Indian banking.

Figure 1: Gross Non-Performing Assets across Bank and Bank Groups



Notes: The gross NPA ratio is calculated by dividing total gross NPAs by gross advances.

Source: Kumar et al. (2022)

Historically metals have played a key role in advancing economic development. Given the wide range of economic activities that rely on steel, the metal has always enjoyed a hegemonic role within the industry. Due to its pivotal role in growth and development, several policies and important reforms have been implemented to enhance the steel industry. After India's steel industry was delicensed in 1991, iron and steel prices were deregulated in 1992. Currently, India is the second-largest steel producer in the world and steel contributes around 2% of the country's total gross domestic product (GDP)⁵.

In a globalised world with few trade barriers, domestic prices move in sync with international prices subject to exchange rate movements⁶. If international prices decline and the exchange rate does not

⁵ <https://pib.gov.in/newsite/PrintRelease.aspx?relid=153661>

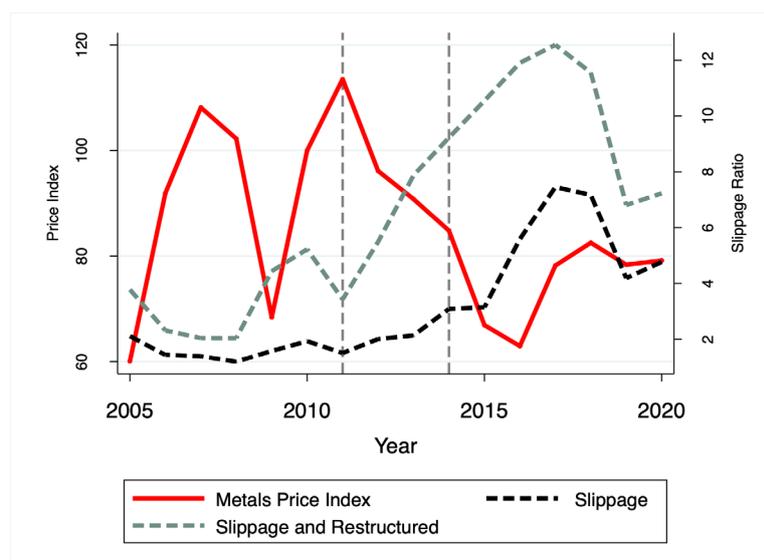
⁶ Domestic prices in rupee terms is the product of international dollar prices and the bilateral rupee-dollar exchange rate. This implies that domestic inflation is the sum of international inflation and the percentage change in the exchange rate. A higher depreciation of the rupee can keep domestic prices increasing in spite of falling international prices.

depreciate significantly, domestic prices will decline too. These price declines affect the nominal profitability of firms adversely, and in a world of nominal debt contracts could cause firms to default on their debt obligations. Conversely, inflation reduces real debt burden and therefore reduce bankruptcy. Brunnermeier et al. (2023) show this transmission of increased price level in the real economy using data for the period during the German inflation in 1919-1923. Since India is not a major commodity exporter, we could deduce that reduced commodity prices would benefit Indian consumers. But that is not true in general. We find a strong correlation between international prices and profitability in several industries including metals as a whole, and iron and steel in particular.

The increase in NPAs after 2011 had a significant impact on financial intermediation and economic growth. As a result, it is critical to understand the primitive factors that made loans unserviceable and ultimately accumulated as NPAs in banks. The strong negative correlation between global commodity prices and profitability in India's metal sector, along with a rise in NPAs from 2011 on, with a significant concentration of defaults in the metal industry, seem more than coincidental. There appears to be a credible route for understanding the creation of NPAs in the Indian banking sector. Figure 2 shows Indian NPAs and the metal price index during 2005-20: the correlation between the two is negative and significant. Since the start of the pandemic commodity prices had been rising. The Russia-Ukraine War added on to this issue. Between 2020-22 commodity prices rose by over 80% and metal prices surged by over 105%. "The unexpected surge in metal and commodity prices following the Russian invasion of Ukraine inadvertently provided support to certain infrastructure, metal, and energy sector corporates, who were sizable contributors to the bad debts" (Agarwal, 2023, p. 84).

Since NPAs are made up of a stock variable, we use two other measures of flow variables – the flow of NPAs termed 'slippage,' and 'slippage+restructured' which is the sum of the slippage and the stock of restructured assets, as we cannot obtain the flow of restructured assets.⁷ The slippage ratio is defined as new additions to NPAs divided by standard advances. To calculate standard advances, we subtract gross NPAs from gross advances. Slippage+restructured is defined as the sum of new additions to non-performing and restructured assets divided by standard advances.

Figure 2: Slippage and the Metal Price Index



Notes: The slippage ratio is a flow measure of NPAs. It is calculated as new NPAs accumulating in a particular year divided by standard advances (gross advances–gross NPAs). Slippage and restructured is the annual average of individual ratios across banks and is calculated as the sum of new NPAs and restructured assets divided by standard advances.

Source: World Bank and Reserve Bank of India.

⁷ Slippage refers to fresh addition to NPAs during a given financial year. Restructured loans are those where borrowers in financial trouble revise the terms of their loans with banks to avoid default.

Our study contributes to the research that links commodity prices, sectoral lending, and price decline to the insolvency of firms and an increase in NPAs in banks. Rajan and Ramcharan (2015) give very credible evidence of the adverse outcomes of an exogenous change in land prices using US data. They unravel the causes for and consequences of the cyclical nature of farmland prices prior to the Great Depression. A negative economic shock led to a larger decline in land prices that caused defaults and a large number of bank failures.

The concentration of bank credit in specific sectors can be problematic. By spreading loans across various sectors and types of borrowers, banks minimise their exposure to a single industry or borrower, thus reducing the impact of potential defaults from sector-specific shocks. Diversification is always good in case of risky assets. Agarwal et. al (2020a) show how bank lending behaviour changes when a large proportion of borrowers face a common negative shock. Using data from Mexican banks they analyse the impact of the sharp fall in energy prices in 2014. They contend that a decline in energy prices caused banks with higher exposure to the sector to lower their lending standards and further increase their lending. This is because in such a situation, banks have reduced bargaining power. During the energy price bust, the working capital and financial needs of energy-producing firms outpaced their expected revenues. Thus, to prevent these firms from failing and to help them maintain their regulatory ratios, banks increased their lending to them. This, contrarily leads to an increase in the financial stress of more-exposed banks. Based on accounting observables, one may be tempted to classify these as zombie lending or bad practices by the involved banks which is not true. Eberhardt and Presbitero (2021) present cross-country evidence on the effects of commodity price volatility on a banking crisis by creating a country-specific aggregate commodity price index. They show how variations in commodity prices can explain variations in output. They go on to assert that the main channel through which commodity prices affect the real economy is through their negative effect on bank balance sheets and financial stability.

The novelty of our work lies in the use of very disaggregated data on sectoral lending by banks and prices associated with each sector. This is an improvement on the aggregate exposure indices based on country-level commodity exposure in Agarwal et. al (2020a) and Eberhardt and Presbitero (2021). It is essential to understand the distinction between deflation and disinflation. In this paper we deal with a fall in commodity prices, which is deflationary in nature, and the consequences of which are very different from a fall in the rate of growth of an increase in prices (disinflation). A steep reduction in commodity prices over a long period, such as seen during 2011-16, can create a huge deviation in actual prices and projected prices, on the basis of which business decisions are made, and can be consequential to borrowing firms and lending banks⁸.

We use a difference-in-differences design to obtain the main results in this paper. Based on banks' sectoral lending (metals, iron and steel and drugs and pharmaceuticals) in 2011 we classify banks into two (three) groups – exposed and non-exposed (exposed, slightly exposed and highly exposed) – in these sectors. The exposed banks are treated banks (chosen based on the proportion of their lending to the iron and steel sector) and the other banks are in the control group. We choose 2011 as the intervention year, as commodity prices started declining then. We find that the assumption of a parallel trend (no difference between exposed and non-exposed banks before the commodity price crash) is satisfied in all the difference-in-differences regressions carried out in this paper.

The results obtained in this paper suggest that, compared to non-exposed banks, banks that had been exposed to the metal sector experienced a significantly higher build-up in NPAs after the metal price crash of 2011. We also find that the intensity of bank exposure to the iron and steel industry is important – highly exposed banks declared significantly higher NPAs compared to slightly exposed banks – and hence these are causal estimates. We obtain similar results for metal

⁸ Historically, emerging nations have been more likely to suffer adverse effects from external shocks (Deaton, 1999) including commodity price shocks.

exposure, but exposure to the drugs and pharmaceuticals industry does not have any role to play in the generation of NPAs. We show that unlike iron and steel, prices in the drugs and pharmaceutical sector have been steadily increasing over the years. Taken together, these results imply that exposure to sectors which experienced a sharp price decline led to the creation of NPAs for exposed banks.

All the robustness exercises we carry out show the unambiguous effects of a decline in metal prices on NPAs in Indian banking. We also show that the share of PSB lending to the iron and steel industry as a proportion of their total lending was almost twice that compared to private banks, which explains their higher build-up of NPAs relative to private banks.

We explore the source of the decline in metal prices in India's domestic market and conclude it was driven by a decline in global prices, predominantly by the prices of Chinese imports. We also test the zombie-lending argument by estimating a model of financial productivity on the lines of Whited and Zhao (2021) and find that data does not support this argument; hence we argue that a large decline in exogenous prices led to the build-up of NPAs in India's banking sectors, which was independent of zombie lending and poor governance. We find that a sharp decline in metal prices significantly reduced the profitability of non-financial firms in the metals sector and affected their loan repayment capacity. Also, as expected, a decrease in commodity prices led to a decline in profits in general, with defaulting firms experiencing an even larger decline in profitability.

The rest of the paper is structured as follows. Section 2 explains the data. Section 3 explains the research design used and provides evidence that the decline in metal prices created NPAs in Indian banks. It also attempts to estimate the aggregate effect of the price crash on NPAs. Section 4 explores the link between a price shock and profitability. Section 4 also provides evidence based on hand collected data of defaulting firms to indicate that defaulting firms experienced a significantly higher decline in profitability after the 2011 price crash. The final section provides concluding remarks and policy implications.

2. Data

We use a range of (micro and macro) data in the analysis. International commodity prices are from the World Bank's Pink Sheet which lists disaggregated prices and indices for commodities, including metals and food. The annual Indian rupee-dollar bilateral exchange rate, also from the World Bank, helps convert international prices into domestic currency, so we can compare international and domestic market prices. We use various sources for Indian data, including the National Accounts Statistics (NAS), the Ministry of Commerce and Industry (for wholesale price indices [WPIs]), and ProwessIQ and Yahoo Finance (for stock price information). We also collated data from the newsletters of the Insolvency and Bankruptcy Board of India (IBBI) related to firms admitted under the bankruptcy process. These data are unique as they list firm-level defaults, which we map to the respective sectors. We hand-mapped firms in the IBBI database to ProwessIQ to obtain their accounting information, which helped us decipher the difference between defaulting firms and non-defaulting firms in the metal sector. We also use firm-level data from CMIE's ProwessIQ to obtain all the other information on non-financial firms.

Besides macroeconomic and non-financial firm data, we obtain bank-level data from the RBI which covers all scheduled commercial banks in India. For our analysis, we exclude small finance banks, banks with total assets below Rs. 10,000 crores, and those whose credit-deposit ratios exceed 100 in most years. The banks remaining in our dataset account for over 90% of the total gross advances by all banks. The sectoral bank-level credit data is partly hand-collected, while the rest is from CMIE's ProwessIQ.

A critical distinction in the RBI's database for bank-level data on bad loans is between NPAs (the flow measure we designate as 'slippage') and restructured assets. Our analysis covers the period

from 2008 to 2020. Due to regulatory forbearance mentioned before, it is likely banks could have classified NPAs as restructured loans during this period, as restructured assets did not require the same level of provisioning as slippage. Therefore, in addition to slippage as a measure of flows, we also perform robustness checks of our results using ‘slippage+restructured assets’ as another measure of the flow of NPAs. We obtain the 6-digit trade value and volume data from UN Comtrade and WITS. This is used to estimate the exchange rate pass-through to dollar prices.

3. Exposure to the Iron and Steel Industry and Non-Performing Assets

3.1 Research Design

A preliminary analysis of the data on sectoral lending and NPAs of banks revealed some interesting patterns. By the late 2000s, most private banks were focused on retail lending, whereas public sector banks (PSBs) had a larger share of lending to industries (see Appendix G). The data suggest that after the 2014 commodities price crash, banks that had lent to industries had higher NPAs than other banks. Even within industries, in some sectors such as metals, textiles, and so on, high NPAs in one bank were indicative of high NPAs in other banks as well. This suggests that the source of the problem was sector-specific and had less to do with the ownership of bank – i.e., public or private.

NPA ratios in the Indian economy began to climb after 2011 and accelerated after 2014 (Figure 1). The Pillar 3 disclosures (as a part of the Basel norms) give us details on sectoral lending. The paucity of historical sectoral lending data constraints us from extending our analysis further back in time. But data from IBBI suggests that the metals sector experienced the highest amount of bankruptcy. Hence, we estimate the effects of exposure in the metal sector on banks’ total NPAs.⁹

We set up a classic 2x2 difference-in-differences analysis. For this, we split banks into two groups, exposed and non-exposed, based on their exposure to the iron and steel industry in 2011. In that year, the share of advances by exposed banks to the iron and steel industry is greater than the average share for all banks lending to the iron and steel industry. Non-exposed banks had below-mean exposure to that industry in 2011. We also create an alternative grouping of banks based on different quartiles of their exposure distribution. Since international commodity prices started declining from 2011 on, we take 2011 as the cut-off period to analyse the effects of the fall in commodity prices on NPAs. ‘Post’ is a dummy which takes the value 1 for the years after 2011 and 0 before.

$$NPA_{it} = \beta_0 + \beta_1 \times Post + \beta_2 \times Exposed + \beta_3 Exposed \times Post + u_{it}$$

$$E(NPA_{it}|Post = 0, Exposed = 0) = \beta_0$$

$$E(NPA_{it}|Post = 0, Exposed = 1) = \beta_0 + \beta_2$$

$$E(NPA_{it}|Post = 1, Exposed = 0) = \beta_0 + \beta_1$$

$$E(NPA_{it}|Post = 1, Exposed = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3$$

⁹ Appendix H presents the sectoral exposure of ICICI Bank (a private bank) in the late-1990s and early-2000s. These were obtained from the bank’s SEC filings. The commodity price crash of the late-1990s created a significant amount of NPAs for the bank as it had a significantly higher exposure to the metals sectors over that period. The bank subsequently significantly reduced its share of loans to commodity-sensitive sectors.

The difference in NPAs between exposed and non-exposed banks before 2011 is given by $E(NPA_{it}|Post = 0, Exposed = 1) - (NPA_{it}|Post = 0, Exposed = 0) = \beta_2$. $\beta_2 = 0$ implies that before the commodity price crash, NPAs in exposed and non-exposed banks were, on average, similar. Having $\beta_2 = 0$ is essential for causal inference about the effects of metal prices on NPAs as it rules out any prior difference between exposed and non-exposed banks. This is analogous to the parallel trend assumption but not the same. The difference in NPAs between exposed and non-exposed banks after 2011 is given by $E(NPA_{it}|Post = 1, Exposed = 1) - (NPA_{it}|Post = 1, Exposed = 0) = \beta_2 + \beta_3$. The difference-in-differences estimator β_3 , is the difference between two differences, i.e., the difference between exposed and non-exposed banks before 2011 and after 2011. We also estimate models with two treatment groups and one control group; the treatment effect is similarly calculated for both treatment groups and compared to the control group.

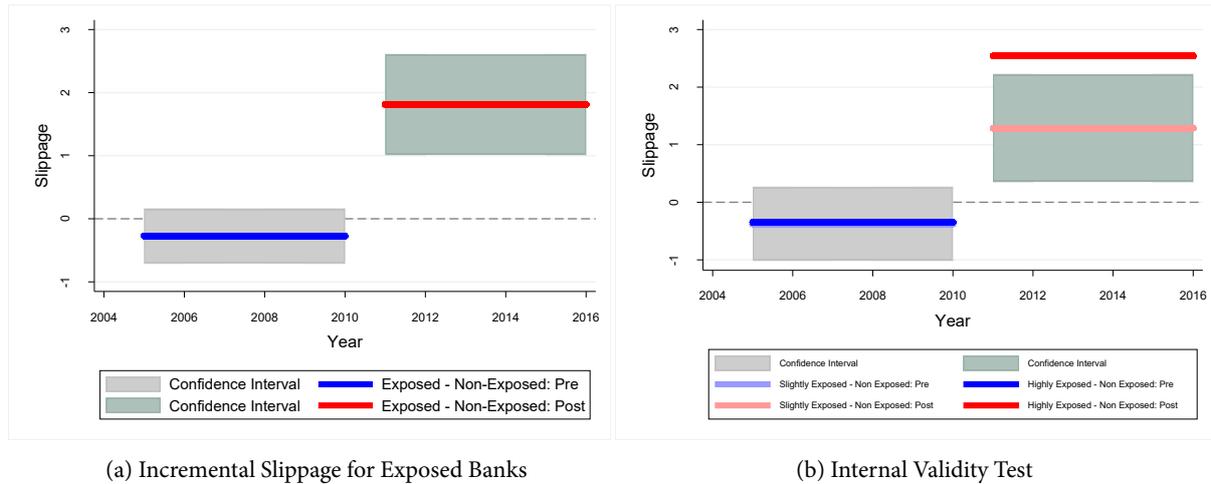
Is it sufficient to make a causal claim?

There are several advantages to the research design outlined in the previous section. First, all the aggregate national and international variables are identical for both groups of banks. Therefore, the absence of these is not likely to cause our estimator, β_3 , to be biased. In other words, the marginal effect of any exogenous macroeconomic variable will be the same for both groups of banks, and will therefore not result in differential NPAs across the two groups. Second, our results are unlikely to be influenced by changes in bank lending behaviour post-2011. Even if changes in lending behaviour, such as zombie lending, did create NPAs, our model design will capture NPAs resulting from sectoral lending and prices. However, bank-level variables apart from exposure could be necessary for the evolution of NPAs, so we control for these variables, such as bank size and profit ratios. The time-invariant bank heterogeneity is not a concern for causing a bias in our estimator. Despite taking care of these concerns, there is still the possibility that the correlations between our variables are merely coincidental. In order to rule this out, we estimate several additional models and assert a causal relationship between exposure to the iron and steel industry in 2011 and the average NPAs during 2011-16.

3.2 Results

Baseline

Since we compare averages across two time periods, we analyse only slippage, which is fresh additions to NPAs. Any restructured assets are likely to be classified as slippage (if they are not likely to be recovered) during the time under consideration. Hence, we argue that slippage is the key variable for a 'before' and 'after' comparison.

Figure 3: Incremental Slippage for Exposed and Non-Exposed Banks

Notes: (a) represents β_2 and β_3 from. $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) is the difference between NPAs of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 ($+ \beta_2$). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. Post is a dummy which takes the value 1 for the years between 2011 and 2016.

(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$ and β_{32} from and $Slippage_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are the differences between the NPAs of $Exposed_1$ and $Exposed_2$ for non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the differences in the NPAs of $Exposed_1$ and $Exposed_2$ for non-exposed banks after price crash in 2011 relative to before the crash. $Exposed_1$ are banks with exposure to the iron and steel industry between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with an exposure to the iron and steel industry beyond the third quartile of the exposure distribution. Slippage is the fresh additions to NPAs.

Source: RBI, Bank Annual Reports

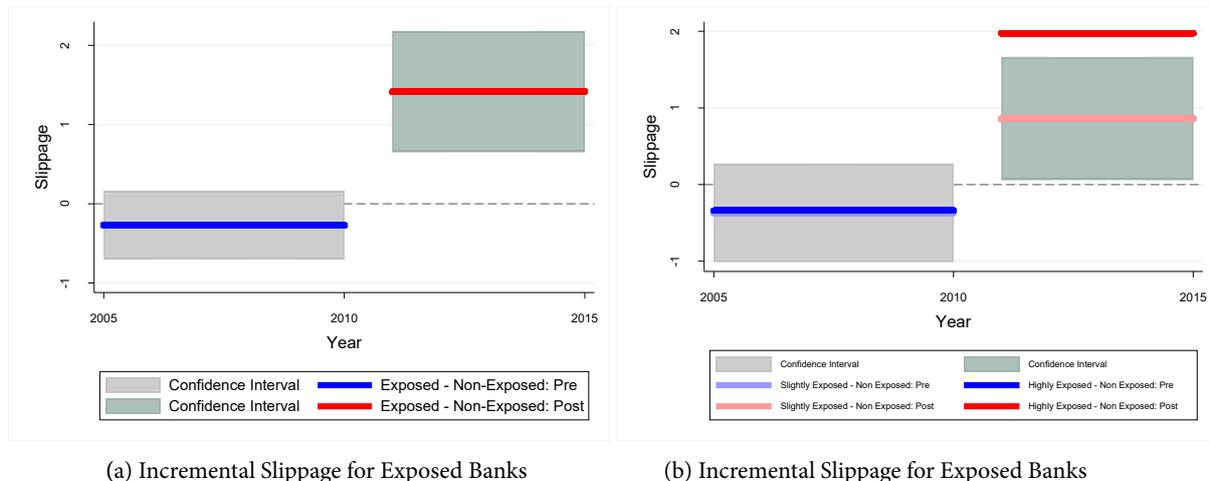
Figure 3 (a) shows the incremental slippage of exposed banks relative to non-exposed banks before and after 2011. Pre-2011, exposed and non-exposed banks had statistically similar slippages, but after 2011, we see that the slippage of exposed banks was about 2% higher than the slippage for non-exposed banks. These results confirm that both groups of banks exhibited similar slippage ratio behaviour between 2005 and 2010, but there was a significant difference in slippage between the two groups after 2011. This period corresponds to a reversal of the uptrend in international commodity prices which started after 2011. Hence the results suggest that the slippage of banks exposed to the metals sector increased significantly after the metal price crash in 2011, compared to banks with little exposure to the metals sector.

For this claim to be causal, it must be internally consistent, i.e., higher exposure to the metal sector must lead to higher slippage. We create three groups of banks – non-exposed, slightly exposed, and highly exposed – based on their advances to the iron and steel industry in 2011. Non-exposed banks are those with less-than-median exposure to the industry in 2011; slightly exposed banks had exposure between the second and third quartile of the exposure (iron and steel) distribution in 2011; and highly exposed banks are those with exposure above the third quartile in the exposure (iron and steel) distribution in 2011. Figure 3(b) shows the results for the three groups. We find that pre-2011 all three groups of banks have slippage ratios, but post-2011, the slippage ratio of slightly exposed banks (represented by the light orange line) is a little over 1% more than for non-exposed banks. Whereas the slippage ratio for highly exposed banks (represented by the red line) is over 2% higher than for non-exposed banks; further, the slippage of highly exposed banks is outside the confidence band for the difference between the slightly exposed and non-exposed banks. This suggests that higher exposure had indeed led to higher NPAs.

Assets Quality Review and Non-Performing Assets: Measurement Issue

A few years after the commodity price crash in 2011, it became clear that banks were facing a problem with their balance sheets. The RBI undertook an asset quality review (AQR) in FY2015-16, which involved auditing the books of banks to ascertain the actual quantum of NPAs in the banking system. The post-treatment period in the previous regression was between 2011 to 2016 as commodity prices started decreasing in 2011 and reached their lowest point in 2016, after which they started moving up again. Since the post treatment period includes years of AQR, it could be argued that the above results might be contaminated due to the AQR. To confirm the validity of the results, we run the same regression, with the dummy variable $post = 1$ for the years between 2011 and 2015. The results, given in Figure 4, show that even before the AQR was initiated, exposed banks experienced a significant increase in their slippage ratios: the slippage ratio for exposed banks, between 2011-15, on average, is nearly 1.5% higher than for non-exposed banks. We also perform an internal validity test for the same time period [Figure 4(b)]. The orange and red lines give us the incremental slippage of slightly exposed and highly exposed banks, over non-exposed banks, respectively. The graph shows us that while all three bank groups had similar slippage ratios before 2011, the ratios diverged between 2011 and 2015. In the period 2011-15, the slippage ratios for banks which were slightly exposed to the iron and steel industry were a little under 1% higher than the ratios for non-exposed banks. In the same period, highly exposed banks had 2% higher slippage ratios than non-exposed banks. Our results are consistent even when we consider observations up to 2015 or 2016, and are therefore not confounded by the AQR.

Figure 4: Incremental Slippage for Exposed Banks (Pre-AQR)



Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) is the difference between the NPAs of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. $Post$ is a dummy which takes the value of 1 for the years between 2011 and 2015.

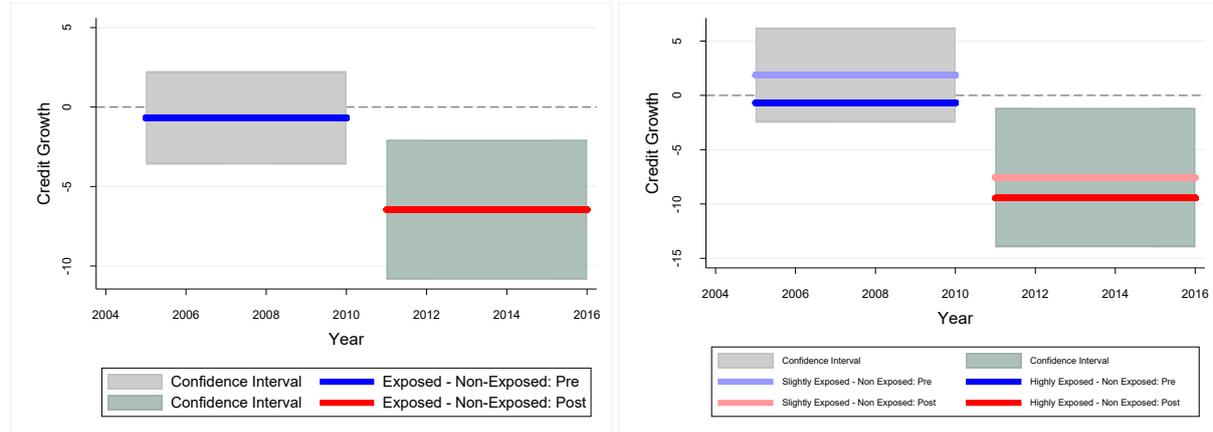
(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$ and β_{32} from $Slippage_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are the differences between the NPAs of $Exposed_1$ and $Exposed_2$ banks and non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the differences between the NPAs of $Exposed_1$ and $Exposed_2$ and non-exposed banks after 2011 and before 2011. $Exposed_1$ are banks with exposure to the iron and steel industry between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with exposure to the iron and steel industry beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

Lending Boom and Non-Performing Assets

Along with the commodity boom, the 2000s was also a period of very high growth in credit and real GDP. It was a period of investment-led growth, which increased the investment- to-GDP ratio significantly (see Subramanian and Felman, 2019). The investment boom may have caused hot lending, which later resulted in the build-up in NPAs.

Figure 5: Incremental Growth in Advances for Exposed Banks



(a) Incremental Growth in Advances for Exposed Banks versus Non-Exposed

(b) Incremental Growth in Advances for Exposed Banks versus Slightly Exposed and Non-Exposed

Notes: (a) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between growth of advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference of differences in the growth of advances of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_3). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2016

(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$ and β_{32} and $GAdvances_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. from β_{21} , and β_{22} , (light blue and blue lines) are differences of growth of advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference in differences of the growth in advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 before 2011. $Exposed_1$ are banks with exposure to the iron and steel industry between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks having exposure to the iron and steel industry beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

We extend our 2x2 difference-in-differences model to estimate the effects on the credit growth of banks:

$$GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$$

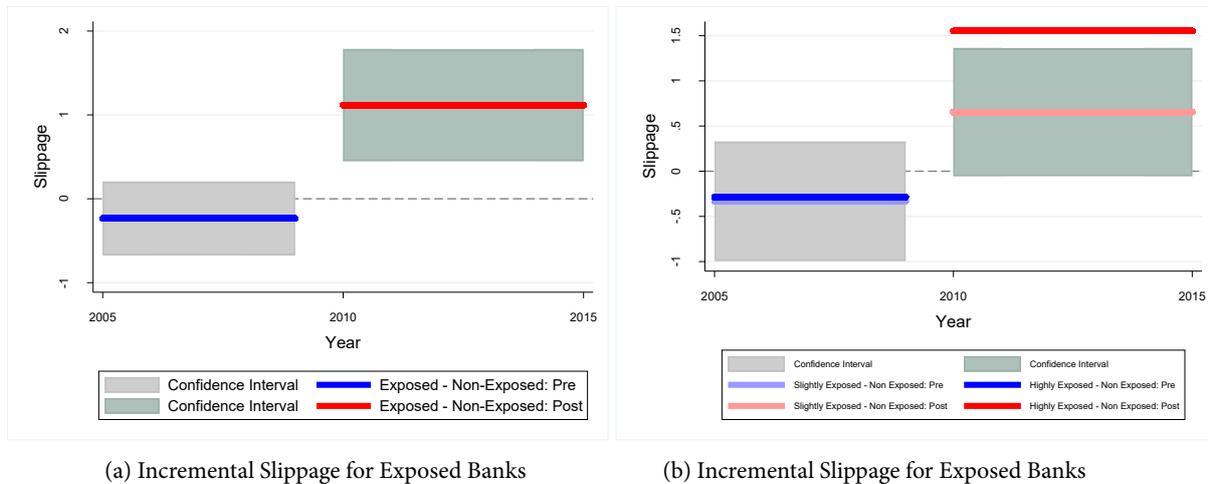
Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. $Post$ is a dummy which takes value 1 for years between 2011 and 2016. Figure 5(a) shows that while credit growth between 2005 and 2010 was the same for the two bank groups, there were significant differences post-2011. Hence, imprudent bank lending does not appear to have contributed to an increase in slippage, which seems to have been driven by commodity prices. After the commodity price crash, NPAs of the exposed banks increased. Due to the unavailability of capital, they were forced to reduce their credit growth, which fell to almost 7% lower than that of non-exposed banks. Gambacorta, L. & Mistrulli (2004) provide evidence on the importance of bank capital for their lending decisions as banks have maintain a certain proportion of risky assets as capital popularly known as Capital to Risk (Weighted) Assets Ratio (CRAR). Meh and Moran (2010) provide evidence about another channel through which capital play important role in lending decisions. They argue that capital affects the ability to attract loanable funds. Figure 5(b) gives these results for the three groups, and again we see that slightly and highly exposed banks

experience credit growth that is similar to the non-exposed banks before 2011. Post-2011 the credit growth of slightly exposed banks and highly exposed banks was lower than the non-exposed banks. Further, the decline in credit growth was higher for the highly exposed banks compared to the slightly exposed banks, but the difference between the slightly and highly exposed banks was not statistically significant.

Falsification Test

In the difference-in-differences study, we take 2011 as the year of treatment, as this was when global commodity prices began reversing their trajectory. So observations pertaining to the prior year are considered as pre-treatment and observations for 2011 and beyond are considered post-treatment.

Figure 6: Validity of Treatment (Falsification Test)



Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2010. The red line (β_3) is the difference between NPAs of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are those that had above-mean exposure to the iron and steel industry in 2011. $Post$ is a dummy which takes the value 1 for years between 2010 and 2016.

(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$, and β_{32} from $Slippage_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$ and β_{22} (the light blue and blue lines) are the differences in NPAs of $Exposed_1$ and $Exposed_2$ from non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference-in-differences in the NPAs of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 and before 2011. $Exposed_1$ are banks with exposure to the iron and steel industry between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with exposure to the iron and steel industry beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

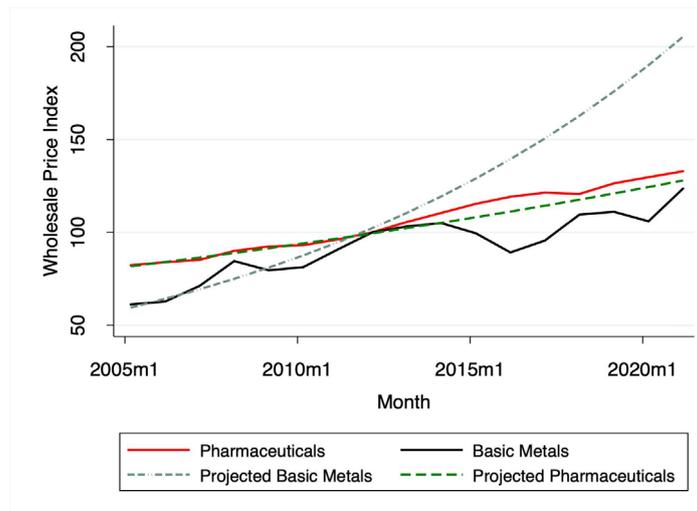
To show that 2011 is a valid treatment year, we use a falsification test, by preponing the treatment year to 2010. If 2011 is a valid treatment year then preponing the treatment by a year adds additional observations from pre-treatment years. This must weaken the average treatment effect, as now untreated years are considered as treated. This is another variant of the parallel trend, which would imply that adding untreated years to treated years would reduce the average treatment effect.

Figure 6 (a) shows the incremental slippage for exposed banks relative to non-exposed banks pre- and post-2010. We see that before 2010, both groups of banks had no statistical difference in their slippage ratios. However, post-2010 banks which were exposed, on average, had higher slippage ratios than non-exposed banks. Although exposed banks have a higher slippage ratio, comparing this to Figure 3(a) shows that when we prepone our treatment to 2010, on average, the slippage ratios for exposed banks are 1% higher than for non-exposed banks, as against 2% when the treatment year is 2011. The results based on the three groups also confirm that the average treatment effect for both the slightly exposed and highly exposed banks is lower than the one shown in Figure 3(b).

Placebo

A bank's exposure to the metal sector significantly impacts the health of its balance sheets by increasing the slippage ratios. We argue that the exposure to the metal sector caused a significant increase in slippage because the prices of metals declined significantly post-2011. This reduced the profitability of firms in the metal sector and caused them to default on their loans, which had accumulated as slippage for banks. Since the channel is the decline in prices, it must be the case that exposure to a sector for which prices have not declined will not lead to an increase in NPAs. To check this hypothesis, we consider the drugs and the pharmaceutical sector, which faced no price decline (Figure 7).

Figure 7: Wholesale Price Index (Actual and Projected) For Metal and Drugs and Pharmaceuticals

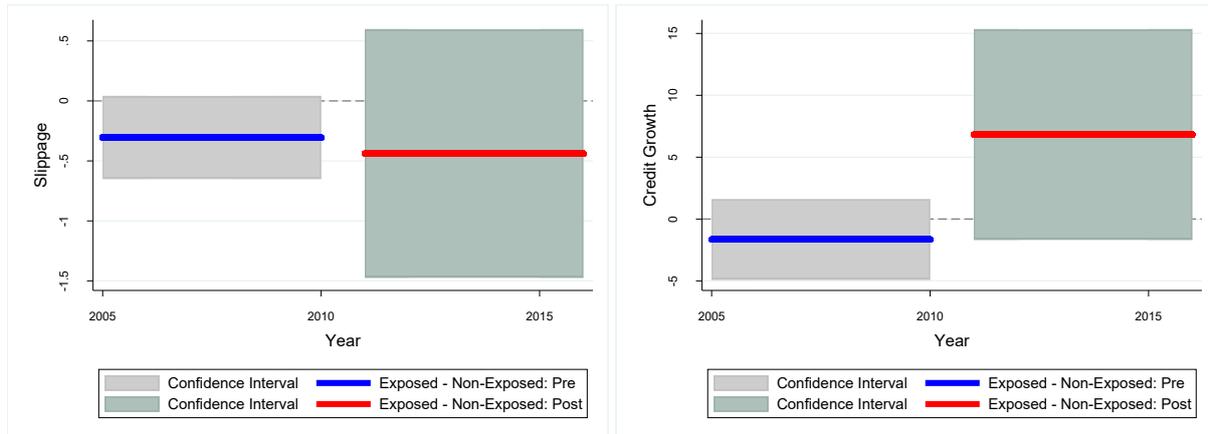


Note: Projected prices are obtained from a regression of log prices on a linear trend based on data from 2004 to 2010.

Source: RBI, Bank Annual Reports

The metal sector's price crash appears even more severe when we compare actual prices with projected prices, based on data from 2004 to 2010. A large number of investment decisions are based on projected prices, so if actual prices are significantly lower than projected prices, the consequences could be severe for borrowers. This is because debt is always denoted in nominal terms, and a large deflation increases the real burden of debt enormously. Similarly, a considerable decline in commodity prices widens the gap between expected and realised sales, which undermines borrowing firms' debt-servicing capabilities and in turn adversely impacts the associated banks. However, this story of defaults did not play out in industries such as drugs and pharmaceuticals, where prices did not deviate from their trend path. Sectoral exposure has a distinct influence on a bank's slippage ratio – one form of manifestation is through price swings. Banks that have lent to industries confronting a sustained fall in the price of their commodities, have experienced higher slippage relative to banks lending to sectors where prices did not deviate from their trend.

Figure 8: Incremental Slippage and Growth in Advances By Banks Exposed to the Drugs and Pharmaceuticals Industry



(a) Incremental Slippage for Exposed Banks

(b) Incremental Growth in Advances for Exposed Banks

Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) is the difference between the NPAs of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2).

(b) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the growth in advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference-in-differences in the growth of advances by exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the drugs and pharmaceutical industry in 2011. $Post$ is a dummy which takes the value 1 for years between 2011 and 2016.

Source: RBI, Bank Annual Reports

To test this, we use a similar 2x2 difference-in-differences (DID) set-up based on banks' exposure to the drugs and pharmaceuticals industry in 2011. We divide the banks into two groups: those with above-mean exposure to drugs and pharmaceuticals in 2011 are categorised as exposed banks; those with below-mean exposure to the sector are categorised as non-exposed banks.

Figure 8 (a) shows the relative slippage ratio of exposed banks compared to non-exposed banks. Banks which have greater exposure to the drugs and pharmaceutical industry have lower (though not statistically significant) slippage pre-2011 relative to banks that are non-exposed. Post-2011, we see that both exposed and non-exposed banks have similar slippage ratios. This essentially means that both exposed and non-exposed behaved the same with respect to their slippage ratios pre- and post-2011. Further, their exposure to the drugs and pharmaceutical industry did not lead to statistically different credit growth for exposed and non-exposed banks after 2011. Therefore, we argue that the decline in prices caused the increase in NPAs for exposed banks post-2011.

3.3 Quantifying the Effects of Exposure to the Metal Sector

The results presented above provide overwhelming evidence that exposure to the metals sector caused an increase in NPAs after the commodity price crash of 2011. Based on the several robustness exercises provided above, it is hard to rule out the causal link. Nevertheless, these results do not provide the extent of the increase in slippage that can be explained using this channel. To measure the aggregate effect, we first estimate a regression given by:

$$NPA_{it} = \beta_0 + \beta_1 Post\ 2011 + \beta_2 Post\ 2011 \times Exposure\ in\ 2011 + \theta_i + \epsilon_{it}$$

The results (presented in Table 1) suggest that a 1% higher exposure to the iron and steel industry led to a 0.32% higher slippage during 2011-16. This implies that a bank with 10% of its advances going to the iron and steel industry has an almost 3.2% higher slippage ratio during 2011-16. This

can have a very large effect as some banks in our sample have more than 20% of their total loans going to this industry. This regression also explains around 50% of the variation in NPAs, which is fairly large given the panel nature of the data. The results further suggest that a 1% higher exposure to the iron and steel industry led to 1.3% lower credit growth during 2011-16. This implies that a bank with 10% of its advances going to the iron and steel industry experienced almost 13% lower credit growth during 2011-16.

Table: 1 Slippage, Growth of Advances and Exposure to the Iron and Steel Industry in 2011

	Slippage	Growth of Advances	Slippage	Growth of Advances
Post 2011	1.481 (1.43)	-9.657** (-3.26)	-0.703 (-0.86)	-8.360** (-2.84)
Post 2011* Exposure in 2011	0.321** (3.42)	-1.297*** (-4.30)	0.242** (2.77)	-0.979** (-3.17)
Constant	2.172*** (5.91)	25.43*** (14.75)	2.172*** (6.04)	25.38*** (15.04)
R^2	0.492	0.341	0.286	0.273
N	376	344	344	312
<i>Bank Fixed Effects.</i>	Yes	Yes	Yes	Yes

Notes: *, **, and *** denote significance at the 5%, 1% and .1% levels, respectively. Estimates using $NPA_{it} = \beta_0 + \beta_1 Post\ 2011 + \beta_2 Post\ 2011 \times Exposure\ in\ 2011 + \theta_t + \epsilon_{it}$. *Post* is a dummy, which takes the value of 1 for years 2011 and beyond. θ_t are bank fixed-effects. The first two columns are for data till 2016. The last two columns are for data till 2015.

Source: RBI, Bank Annual Reports

To further quantify the contribution of commodity exposure to NPAs we estimate two regression equations:

$$NPA_{it} = \beta_0 + \theta_t + \theta_i + \epsilon_{it}$$

$$NPA_{it} = \beta_0 + \beta_1 Post\ 2011 \times Exposure\ in\ 2011 + \theta_t + \theta_i + \epsilon_{it}$$

The first equation gives θ_t which is the year fixed-effects and allows us to understand the evolution of NPAs conditional on bank-level, time-invariant heterogeneity. The second regression gives θ_t which is the year fixed-effects conditional on bank-level time-invariant heterogeneity and also on exposure and its effects post-2011. The difference in the year fixed-effects from these two regressions can be assumed to be the contribution of exposure in the iron and steel industry to NPAs over these years. The red dots show the year fixed-effects of banks with exposure in 2011 and the green line gives the year fixed-effects without exposure. The vertical bars give the confidence intervals for each of these years. The results in Figure 9 suggest that the entire evolution of slippage up to 2015 can be explained by the impact of exposure post-2011. This is because the year fixed-effect is not significant in the presence of exposure till 2015. After 2015, though, almost half of the year fixed-effects can be explained by the exposure in 2011. These results suggest that exposure in 2011 explains up to 50% of the variation in NPAs over the years.

Figure 9: Event Study on Evolution of Slippage in Exposed versus Non-Exposed Banks

Notes: The green line is θ_t from $NPA_{it} = \beta_0 + \theta_t + \theta_i + \epsilon_{it}$. The red line is θ_t from $N\beta_0 + \beta_1 \text{ Post } 2011 \times \text{Exposure in } 2011 + \theta_t + \theta_i + \epsilon_{it}$. The dependent variable NPA_{it} is the slippage ratio defined as new additions to NPAs divided by standard advances. Standard advances is the difference between gross advances and gross NPAs.

Source: RBI, Bank Annual Reports

3.4 Alternative Identification Using a Forward-Looking Variable

So far we have considered the treatment based on mean and median exposure of banks to the iron and steel industry. The increase in slippage in banks due to an increase in the intensity of the treatment (exposure) confirms the causal link between the two, although one can argue that the identification is subjective. To ensure the robustness of our results, in this section, we use an alternative identification strategy. Most banks in our study are listed on the stock exchange, so their stock prices contain information about their exposure. One would expect that banks with greater exposure to the metals sector will have stock returns with higher sensitivity to commodity prices conditional on market or systematic risk. We estimate this sensitivity using the regression given by:

$$\text{Log } SP_{it} = \beta_{0i} + \beta_{1i} \times \text{Log Sensex}_t + \beta_{2i} \text{Log Metal Index}_t + \epsilon_{it}$$

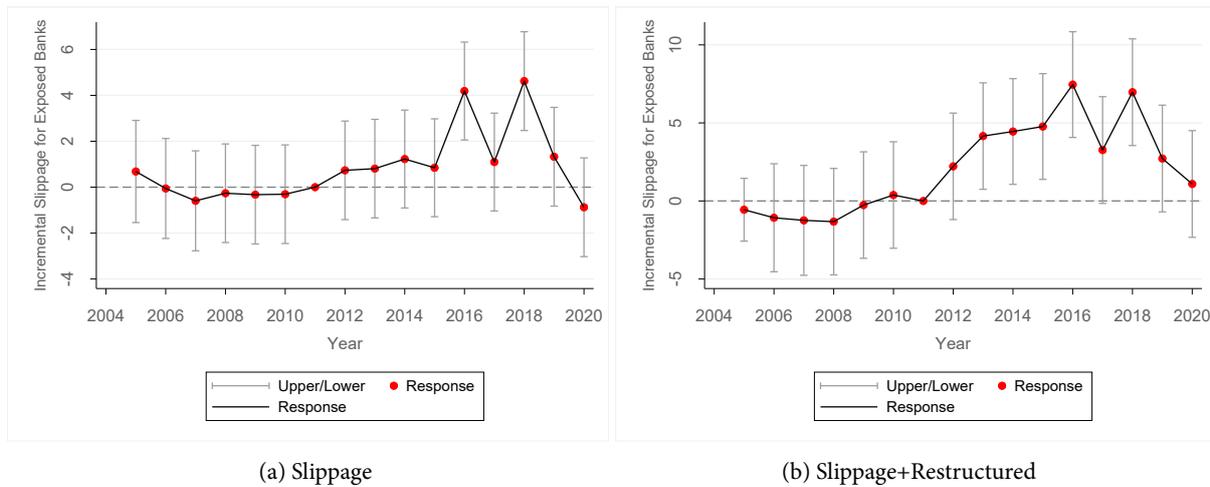
SP_{it} is the log of the stock price of bank i at time t . β_{2i} is the elasticity of the stock price with respect to the metal price index for bank. The Sensex is the Bombay Stock Exchange (BSE) benchmark index and controls for systematic risk. The model above is similar to the multi-factor models of stock returns widely used in the finance literature. The metal index is the metal price index from the World Bank. To estimate elasticity, we use monthly data from 2010 and 2011, i.e., a year before and a year after the metal price collapse. Banks with an elasticity greater than 1 are classified as 'exposed'. Figure 10 present the results from

$$NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{\text{exposed}_y} (\text{Exposed} \times D_y) + \epsilon_{it}$$

$$NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{\text{exposed}_y} (\text{Exposed} \times D_y) + \theta'z_{it} + \epsilon_{it}$$

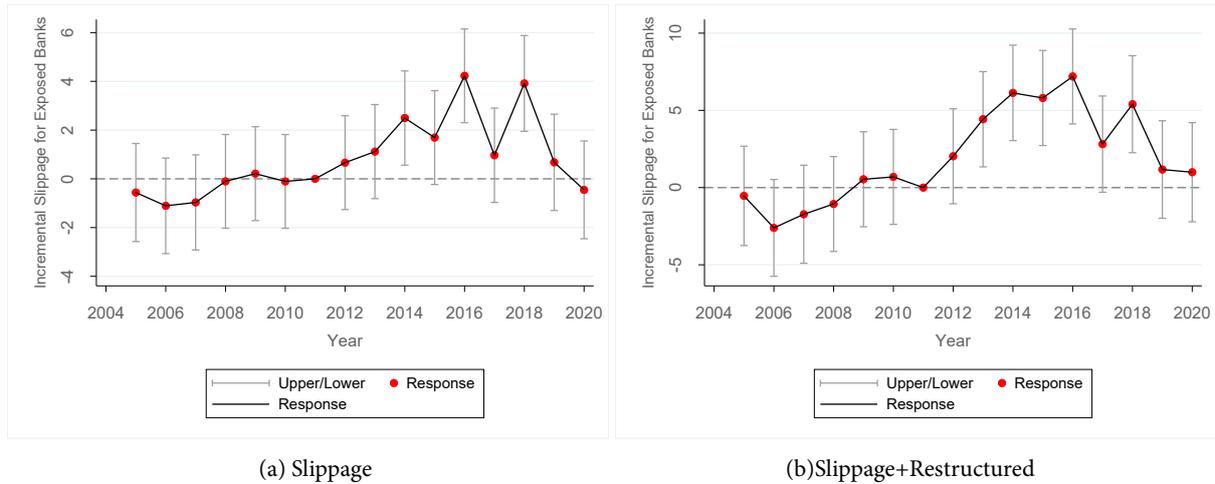
where NPA_{it} is the chosen measure of NPAs; θ_i are bank fixed-effects and θ_y are the year fixed-effects; D_y is the year dummy. This is the famous two-way fixed-effects (TWFE) estimator which is likely to causal effect in the case of a single treatment. θ' is a vector of coefficients and Z_{it} contain bank-level variables which are treated as control variables. The annual evolution of NPAs may depend upon bank-level controls such as profit and size. Less-profitable banks may be reluctant to declare assets as non-performing outright, and may restructure them to begin with. This is because declaring assets as non-performing requires a higher provision and these banks may be constrained by their low profits. Size may be also important for the yearly evolution of NPAs and hence we control for size as well. We use both slippage and slippage+restructured as a measure of NPAs as the event study design allows us to capture their year-wise evolution, unlike the difference-in-differences design used above which only allows us to make before and after comparisons.

Figure 10: Event Study (Slippage and Slippage+Restructured)



Notes: $\theta_{exposed}$ is from $NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{exposed} (Exposed \times D_y) + \epsilon_{it}$. D_y is the dummy variable for each year y . Exposed banks ($Exposed = 1$) are banks whose stock price elasticity with regard to metal prices is greater than one. We calculate elasticity with the metal price index from the individual bank-level regression given by $Log SP_{it} = \beta_0 + \beta_1 \times Log Sensex_t + \beta_2 \times Log Metal Index_t + \epsilon_{it}$. SP_{it} is the stock price of bank i at time t , $Sensex$ is the Bombay stock exchange (BSE) benchmark index, and $Metal Index$ is the metal price index from the World Bank. We use monthly data from 2010 and 2011 to estimate elasticity, which has data from a year before and a year after the metal price crash. The dependent variable NPA_{it} is the slippage and the slippage+restructured ratios. Slippage is fresh additions to NPAs as a share of standard advances, and slippage+restructured is the sum of fresh additions to NPAs and restructured assets as a share of standard advances (standard advance = gross Advances – gross NPA).

Source: RBI, Bank Annual Reports, World Bank, BSE

Figure 11: Event Study (Slippage and Slippage+Restructured)- with bank-level controls

Notes: $\theta_{exposedy}$ is from $NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{exposedy} (Exposed \times D_y) + \theta' z_{it} + \epsilon_{it}$. D_y is the dummy variable for each year y . Exposed banks ($Exposed = 1$) are banks with a stock price elasticity with regards to metal prices greater than one. We calculate elasticity with the metal price index from the individual bank-level regression given. $\text{Log } SP_{it} = \beta_0 + \beta_1 \times \text{Log } Sensex_t + \beta_2 \text{Log } \text{Metal Index}_t + \epsilon_{it}$. SP_{it} is the stock price of bank i at time t , $Sensex$ is the Bombay Stock Exchange (BSE) benchmark index, and Metal Index is the World Bank's metal price index. We use monthly data from 2010 and 2011 to estimate elasticity. This contains data from a year before and a year after the metal price crash. The dependent variable NPA_{it} is the slippage and slippage+restructured ratios. Slippage is fresh additions to NPAs as a share of standard advances. Slippage+restructured is the sum of fresh additions to NPAs and restructured assets as a share of standard advances (standard advance = gross advances – gross NPA).

Source: RBI, Bank Annual Reports, World Bank, BSE

As we can see from Figures 10 and 11, exposed and non-exposed banks had similar levels of NPAs (both slippage and slippage+restructured) before the commodity price crash. Post-2011 the NPAs of exposed banks started to increase compared to non-exposed banks. It is also clear that initially exposed banks had higher slippage+restructured (Figure 11) which later led to statistically higher levels of slippage as well (Figure 10). This makes sense as banks may be inclined to first restructure these assets and later declare them as slippage if nothing works out. This implies that post-2011, exposed banks started with a statistically higher proportion of restructuring compared to non-exposed banks. It is also clear from the above results that profit and size do not affect the results significantly. These are important variables which we expect to have a significant effect on NPAs. Since they do not affect the main results, it is highly unlikely that any other variable would do so. Hence, we argue that the omitted variable bias is unlikely to cause a problem for our research design. Since we use categories based on past data, simultaneity is ruled out.

The results so far present overwhelming evidence that the commodity price crash caused a significant increase in NPAs in the metals sector. It is not clear ex-ante why that should be the case. The decline in commodity prices may have led to a decline in sales prices, but it would also have led to a decline in input costs, such as raw materials. Hence the link from commodity prices to repayment capability of firms in the metal sector is not clear. In the next section, we explore this issue in detail and present evidence of the channel through which a large decline in commodity prices significantly affected the repayment capacity of affected firms and hence generated NPAs in banking.

4. Price Shock, Profitability and Defaults

The results presented in the previous section provide substantial evidence that a large decline in metals prices resulted in a build-up in NPAs for banks which had significant exposure to the metals sector. It is clear from Figure 12(a) that the decline in global prices started in 2011, but its transmission to the Indian economy was delayed. The local/domestic price P is related to the global price, P^* and exchange rate E based on the law of one price given by:

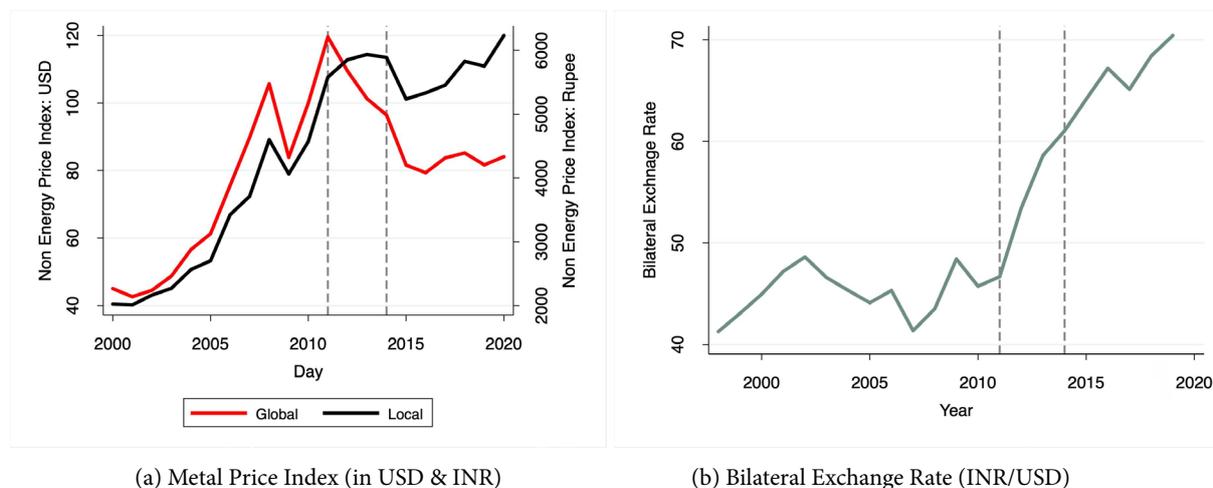
$$P = EP^*$$

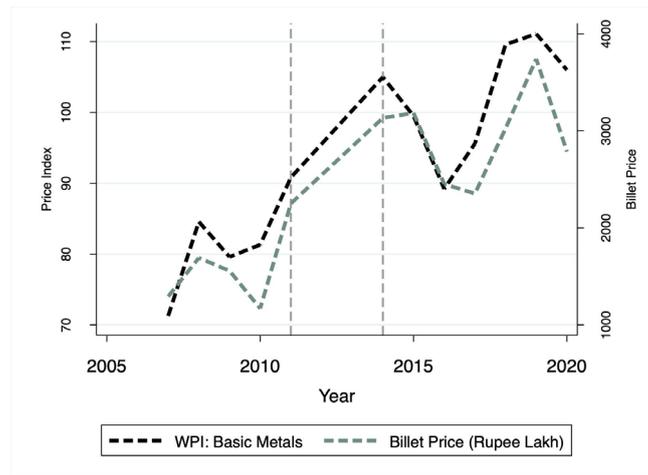
The large decline in domestic metal prices occurred post-2014 as a result of a significant decrease in global commodity prices (predominantly led by China) and a less than proportionate depreciation of the Indian rupee. Based on the law of one price, a decline in P^* if followed by the depreciation of the exchange rate will not lead to a decline in domestic prices. During 2011-14, the decline in global commodity prices was compensated by the steep depreciation of the rupee and a slight increase in the prices of articles from the rest of the world. Appendix C provides evidence that the decline in domestic prices was predominantly driven by the lower price of imports from China.

As micro evidence, we look at the average price of one of the main products in the metals sector, billets, along with the metals component of India's wholesale price index. To obtain the price of billets, we use unique product price data from CMIE's ProwessIQ database. Figure 12 shows that India's wholesale price index for metals began a downward trend after 2014, and the price of billet followed a similar pattern. This substantiates the point made earlier that the decline in global commodity prices translated into a decline in domestic commodity prices after 2014.

Increased productivity may result in a decrease in prices via lowering marginal costs. However, this did not happen here: the global price decline resulted from a massive slowdown in demand for metal products after the North Atlantic financial crisis. As the largest steel producer, China predominantly led global and Indian price movements. One can understand the market power of the Chinese steel firms by some simple facts: in 2014, China produced about 823 million tonnes (MT) of crude steel relative to about 111 MT by the second-largest producer then, Japan. In 2021, China still dominated steel production, producing 1,033 MT, nine times more than India (the second-largest steel producer) at 118 MT.

Figure 12: Some Indian Metal Price Indices and Exchange Rates





(c) Wholesale Price Index (Basic Metals) and Prices of Billet

Notes: The metal price index (from World Bank data) is given in US dollars. The local price index is obtained by multiplying the global price index by the Indian rupee-US dollar exchange rate. India's wholesale price index (WPI) is in Indian rupees, with a base of 2011-12. Billets are one of the main finished products of the metal sector.

Source: World Bank and Reserve Bank of India

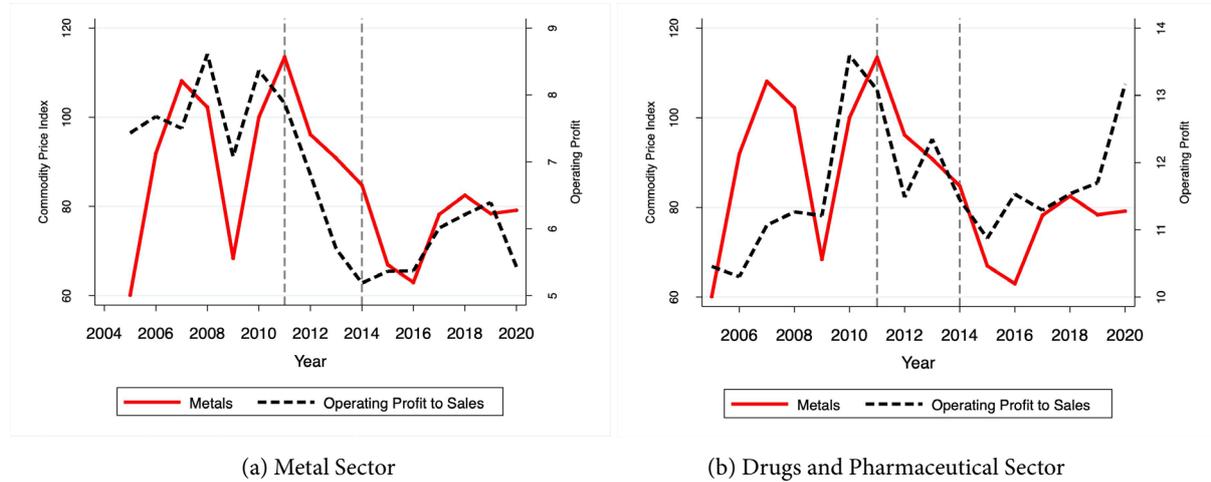
As expected, this sharp demand-driven downturn in prices affected the profitability of firms in the metals sector. The link between commodity prices and profitability is quite apparent in the data. In the late 1990s, the decline in commodity prices during the Asian financial crisis also coincided with an increase in bad loans in banks. This had also occurred during the 2008 financial crisis, when a commodity price decline led to an increase in NPAs (Figure 13). The channel for the transmission of a fall in commodity prices to an increase in NPAs can be seen through the deterioration in the profitability ratios of firms. Commodity prices affect both the costs and revenues of firms. This is why we choose the operating profit ratio, as it is the difference between sales revenues and operating costs, including material costs. The operating profit ratios of firms show a large reduction, indicating that the decline in sales income is significantly greater than the reduction in product cost. The effect of this decline in prices were also faced by subsidiaries of Indian firms abroad. Some of these companies were facing losses as huge as \$1million/day by 2016 (John, 2016). Further, a rise in commodity prices denotes stronger economic growth and demand, so businesses can pass on to consumers the rise in prices of inputs. But during a downturn in prices, firms cannot reduce wages which is a significant component of input cost, hence, wage rigidity can adversely impact profitability. We try to explore this aspect in our forthcoming work. Firms also have significant other fixed costs. The increase in their top line due to an increase in prices is not associated with a concomitant increase in fixed costs, so profitability increases. In contrast, a decline in their top line would mean that profitability decreases as fixed costs remain the same.

In other words, the larger the share of fixed costs for a firm, the greater the sensitivity of its profit to commodity and sectoral prices. Since firms in the metals sector typically have high fixed costs, they experience a significant correlation between sectoral prices and cash flow and profitability. Notably, the fulfilment of debt obligations is contingent on nominal operating profits and cash flows: if these decrease sharply, non-financial firms would find it challenging to fulfil their debt obligations. The commonly used nominal debt contract exacerbates the situation, as in such a cases the real debt burden increases significantly.

As expected, these price declines do not affect profitability in the drugs and pharmaceutical industry [Figure 13 (b)]. To explore the commodity price-profitability link further, we estimate a firm-level regression (Tables 2 and 3). As we can see, an increase in commodity price (metals price) increases firm profitability in the metals sector (Table 2): a 10% increase in a metal's prices increases

a firm's operating profit-to-sales ratio by ~1 percentage point. This effect is quite large given the fact that metal prices increased by more than 75% and declined by more than 33% over a very short period. Further, as we can see, the increase in commodity prices (metal prices) does not affect the profitability of firms in the drugs and pharmaceutical industry (Table 3).

Figure 13: Prices and Profitability (Metals and Drugs & Pharmaceuticals)



Notes: We exclude firms with profits ratios (operating and net) over 100% and less than -100%. For each year, we calculate the mean of the operating profits and the net profit ratios for all firms in the sector.

Source: World Bank, CMIE Prowess and Kumar et al. (2022).

Table 2: Operating Profit to Sales and Commodity Prices in the Metal Industry

	(1)	(2)	(3)
	Operating Profit to Sales	Operating Profit to Sales	Operating Profit to Sales
D. Log Metals	1.859*** (5.82)	2.075*** (6.47)	1.935*** (6.06)
Company Fixed Effects	Yes	Yes	Yes
Log Sales	No	Yes	Yes
Log Fixed Assets	No	No	Yes
Observations	15663	15663	15663

Notes: *, **, and *** denote significance at the 5%, 1% and .1% levels, respectively. Estimates have been obtained from Operating Profit_{it} = $\beta_0 + \beta_1 D. \text{Log Metals} + \beta_2 \text{Log Sales} + \beta_3 \text{Log Fixed Assets} + \theta_i + \bar{i}_{it}$.

Source: CMIE Prowess, World Bank Pink Sheet

Table 3: Operating Profit to Sales and Commodity Prices in the Drugs and Pharmaceuticals Industry

	(1)	(2)	(3)
	Operating Profit to Sales	Operating Profit to Sales	Operating Profit to Sales
D. Log Metals	0.0475 (0.07)	0.697 (1.06)	0.580 (0.88)
Company Fixed Effects	Yes		
Log Sales	No	Yes	Yes
Log Fixed Assets	No	No	Yes
Observations	5736	5736	5736

Notes: *, **, and *** denote significance at the 5%, 1% and .1% levels, respectively. Estimates have been obtained from Operating Profit_{it} = $\beta_0 + \beta_1$ D. Log Metals + β_2 Log Sales + β_3 Log Fixed Assets + $\theta_i + \epsilon_{it}$.

Source: CMIE Prowess, World Bank Pink Sheet

The results presented in Tables 2 and 3 confirm the that India's metal industry is tightly linked to global commodity prices. As global commodity prices crashed in 2011, operating and net profits declined sharply in India's metal industry¹⁰. Even before the pass-through of prices into the domestic economy, Indian metal firms were struggling as their export prices decreased. Later the transmission of commodity prices to the domestic economy exacerbated the situation, and the average net profit in the industry turned negative¹¹.

Figure 14: Profits, Borrowings, and Investments

(a) Fresh Borrowings and Profits

(b) Correlation Between Fresh Borrowings and Fixed Investments

Notes: Fresh borrowings is the cash flow from total borrowings; fixed investment is the cash outflow on the purchase of fixed assets. We have omitted from our analysis firms which have negative sales and fixed assets, and those with operating profits and net profits over 100% and lower than -100%.

Source: CMIE Prowess.

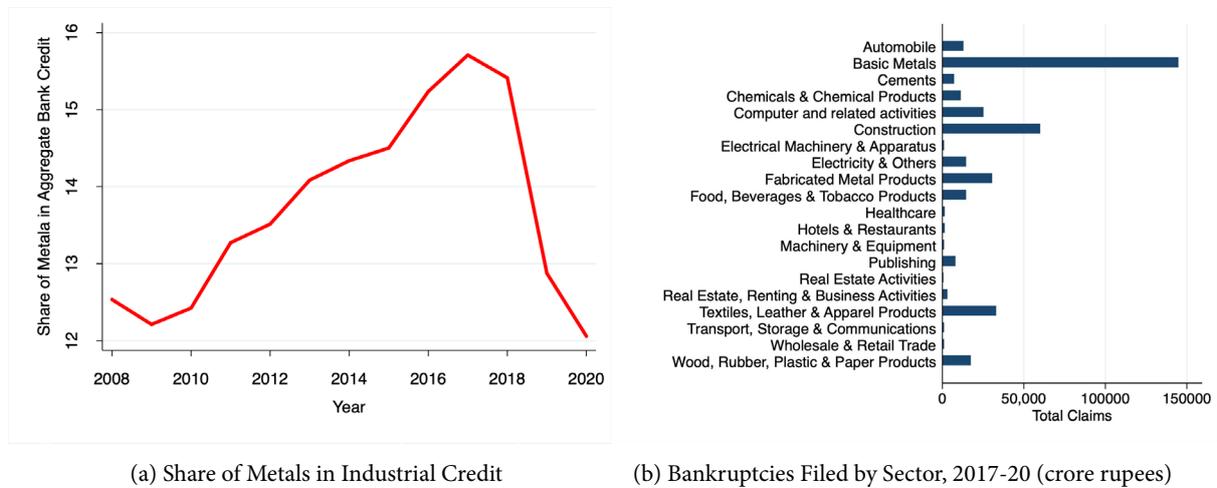
¹⁰ "Our loan portfolio also includes project finance, corporate finance, and working capital loans to commodity-based sectors such as iron and steel, other metals and mining, which are subject to similar and additional risks, as well as global commodity price cycles. For instance, during fiscal 2016, due to a slowdown in global demand for steel, there was a sharp decline in global steel prices, which in turn impacted Indian steel companies. Capacity utilization of steel companies declined and profitability came under pressure. The Government of India announced certain policy measures, including a minimum price for procuring steel from overseas markets, which have benefited the Indian steel sector. However, we cannot be certain that such or any other measures will continue to be introduced by the government in the future. A slowdown in the Indian and global economy may exacerbate the risks for the projects that we have financed."

¹¹ <https://www.barrons.com/articles/higher-commodity-prices-are-good-for-profits-not-bad-51615465806> <https://www.wsj.com/articles/raw-materials-prices-have-surged-corporate-profits-are-likely-next-11618219801>

Figures 14a and 14b indicate further disturbing patterns for the metals sector. The periods of decreasing profits were also periods of increasing credit to the sector and a decreasing correlation between borrowing and investments. This can be seen in the aggregate data as well.

Figure 15(a) shows that the share of credit to the metal sector out of total industrial credit has been increasing over the years, which could suggest possible zombie lending in the industry, as documented in the literature (see Chari et al. 2020). However, Appendix D of this paper presents several results which rule out the presence of zombie lending. We would also like to reiterate that attempts to unearth zombie lending/bad lending practices based on publicly available data are difficult, as bank lending decisions are based on a large amount of private information which is not available to econometricians.

Figure 15: Share of Credit to the Metal Sector and Sectoral NPAs



Notes: The share of metals in industrial credit is obtained by dividing credit to the metal sector by the total industrial credit of scheduled commercial banks. Claims are the total amount admitted in the bankruptcy court during 2017-20.

Source: Reserve Bank of India and the Insolvency and Bankruptcy Board of India (IBBI).

However, such lending could also be based on rational decisions by banks. Agarwal et al. (2020b) suggest that banks with greater exposure to the energy sector increased their exposure to borrowers from this sector at lower lending rates to assist their businesses when energy prices crashed in 2014. It is worth mentioning that it is very difficult to disentangle the genuine illiquidity issue from zombie lending. Our empirical strategy (difference-in-differences) takes this into account, and hence we estimate the effect of commodity prices on NPAs using a framework that is not likely to be contaminated with zombie lending to a large extent.

Figure 15(b) depicts the sector-wise claim amounts filed in the bankruptcy process under the new bankruptcy code from 2017 to 2020. The industry with the largest amounts of claims is metals; textiles, another commodity-sensitive industry, also has significantly higher claims than many others. This gives further credence to our hypothesised link between commodity prices and NPAs in the Indian banking system. In a similar vein, the crash in global cotton prices in 2011 was followed by a significant decline in the price of cotton yarn in India, as is evident from the corresponding wholesale price index.

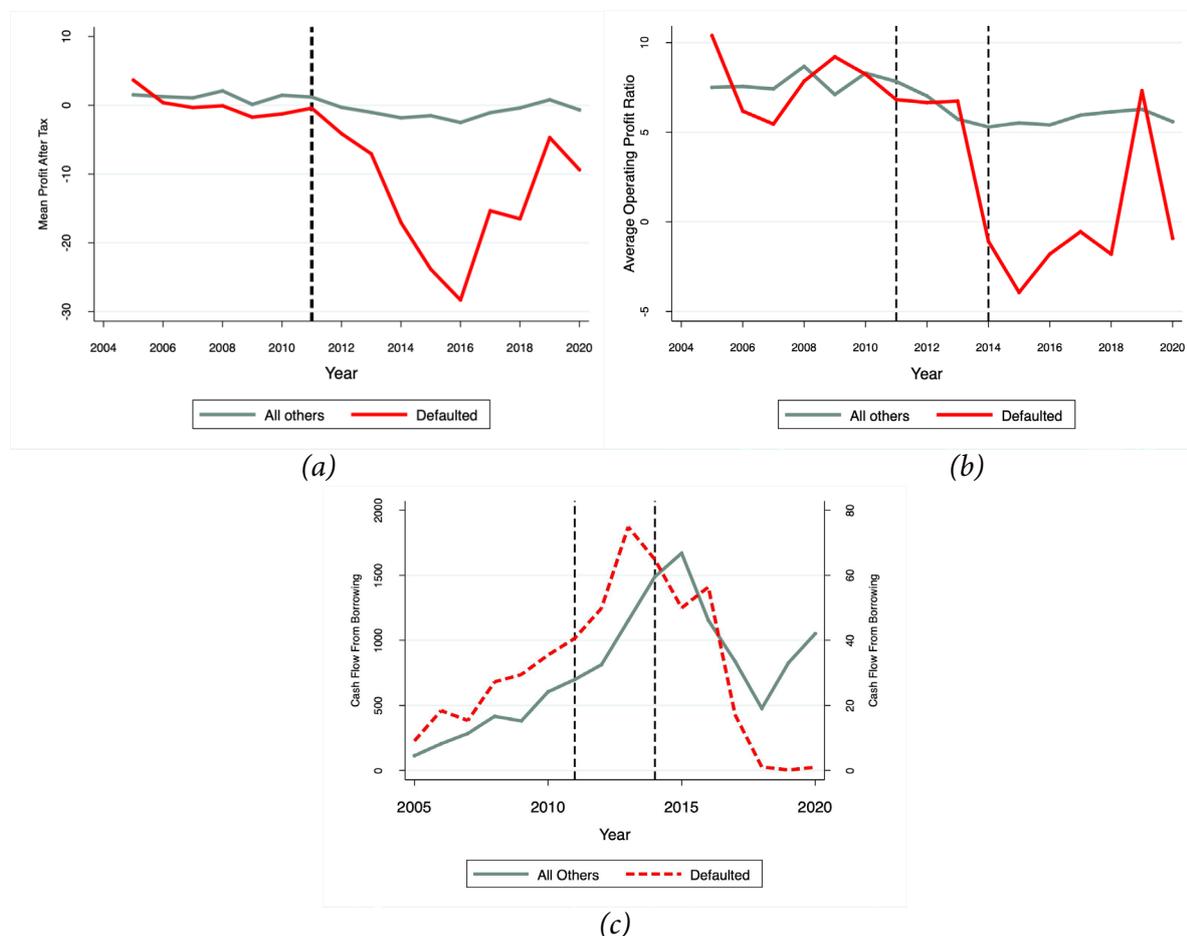
The evidence presented in this section suggests that commodity price shocks affect profitability which can lead to firms defaulting on their loans, which in turn results in higher NPAs in banks. Figures 16 (a) and (b) present additional evidence that adds credence to this channel. The graphs in the figures depict the operating profits, net profits, and borrowings for two sets of firms in the metals sector. We hand-match the firms which filed for bankruptcy in the metals sector [obtained

from the Insolvency and Bankruptcy Board of India (IBBI)] to the Prowess database. These firms are represented as “defaulted”, and all other firms in the metal industry in the database as “other firms”.

During the period of high commodity prices, the average profitability for defaulted firms was similar to that for other firms. In fact, for some years, the average operating profit ratios for defaulted firms was even higher than that for other firms. Once commodity prices started declining in 2011, average profit ratios declined significantly, and when these ratios turned negative, the firms had no option but to default on their loans. Importantly, there was a large degree of heterogeneity in the magnitude of the effect of commodity prices on the default rate: not all firms defaulted due to commodity price shocks, some were more vulnerable to commodity price shock than others. We explore this in a forthcoming work, but present some fundamental intuitive reasons in Figure 17. A firm may experience a worsening its operating profits when its sales price declines if there is an increase in either the share of its raw materials (as a proportion of its revenue) or the share of labour or both. We find that a decline in operating profits for the defaulted firms occurred mainly when there was a significant increase in the labour share. This makes sense as nominal wages are downwardly rigid and it is difficult to lay-off workers. Hence, in the case of an exogenous price shock, labour market power seems to play a critical role in precipitating defaults.

As we can see, borrowing by these firms gives little evidence of bad lending practices by banks (Figure 16). The loans to defaulting firms may have increased during 2011 and 2012 as most large loans are delivered in tranches. Also, it would have been very hard for a banker to foresee the sharp and persistent fall in prices, as shown in Figure 7. However, loans to these firms started declining well before domestic commodity prices began to fall.

Figure 16: Profits and Cash Flow from Borrowings Of Defaulted versus Other Firms



Note: We exclude firms with operating and net profits ratios over 100% and lower than -100%. We calculate the year-wise mean of the ratios for each group. Cash flow from borrowing is the net cash flow from borrowing from all sources and is in billion rupees.

Source: CMIE Prowess and IBBI

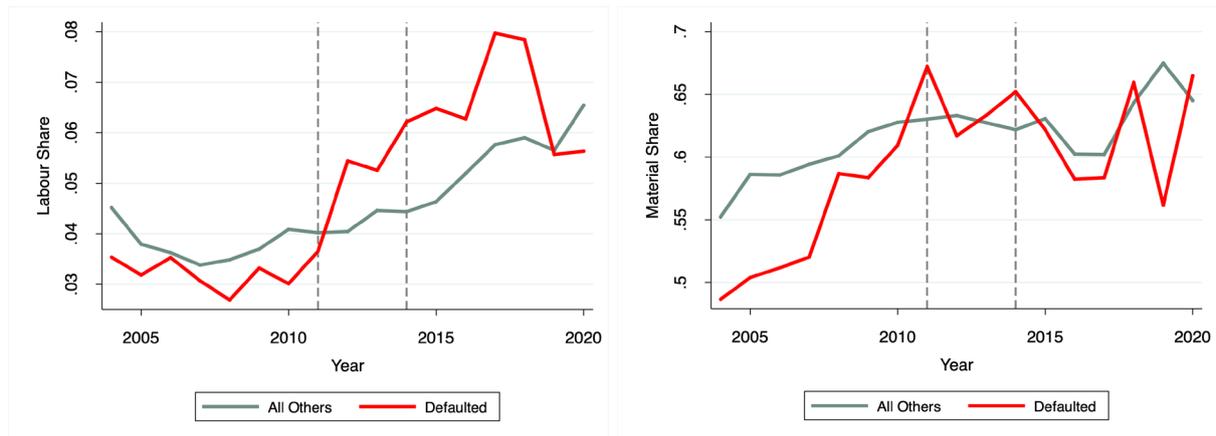
Figure 17: Defaulted versus Other Firms (Labour and Material Share)

Figure 17: We exclude firms with operating and net profits ratio over 100% and lower than -100%. We calculate the year-wise mean of the ratios for each group.

Source: CMIE Prowess and IBBI

5. Concluding Remarks and Policy Implications

India's growth story was starting to look successful in the 2000s before its financial sector started crumbling, burdened by high NPAs and sluggish credit growth. After reaching ~16% (as a % of gross advances) in FY1997, NPAs in the Indian banking sector fell below 3% by 2010, before rising again. The reduction in NPAs coincided with the commodity bull run, and NPAs began rising again only when commodity prices changed their trajectory and started declining. In 2014, when commodity prices sharply declined, NPAs in all the scheduled commercial banks rose from less than 5% to over 15%. Broadly, what starkly stands out is that the rise in NPAs was concentrated across some banks, mainly those with more-extensive lending portfolios in commodity-sensitive sectors, which were adversely affected by the sharp decline in prices.

The debates on NPAs in the Indian banking system tend to be centred on the distinction between the styles of functioning of PSBs versus PVBs, with the former being accused of poor governance, corruption, and zombie-lending which led to the rise in NPAs. Even in the absence of reasonable evidence, these hypotheses have tended to be accepted, which does not make for effective policy making. In appendix F we show that in the 2000s, the PSBs performed better than the PVBs in terms of return on equity and were comparable in terms of return on assets. The big divergence in the performance between the two groups happened in the 2010s, which coincided with the commodity price crash. In the early 2000s, when NPAs started to decline, for some years towards the end of the decade, NPA ratios for PSBs were lower than for the PVBs. Given that poor governance cannot explain the improved performance of PSBs in the 2010s, it is hard to argue that governance in these banks worsened so rapidly. Therefore, we contend that poor governance cannot adequately explain the rise in NPAs. We use systematic empirical analysis to enrich our understanding of rising defaults and NPAs (the twin balance-sheet crisis) in the 2010s. The results obtained in this paper suggest that genuine economic distress due to exogenous factors, that reduce nominal revenue, can render businesses unable to pay their loans because of nominal debt contracts, which increase NPAs in banks. Global commodity prices are one such factor over which neither banks nor firms have any influence.

Using a novel difference-in-differences approach, we find that banks with greater exposure to the iron and steel industry in 2011, but with similar levels of NPAs as non-exposed banks before the decline in commodity prices, had a higher level of NPAs after commodity prices started decreasing in 2011. We show that these results are not driven by the RBI's asset quality review (AQR) in 2015-16, because even during 2011-15, these exposed banks declared significantly higher levels of NPAs compared to non-exposed banks. Since exposure to other industries such as drugs and pharmaceutical did not create NPAs, we argue that the global metal price crash during 2011-16 was a cause of the NPAs in exposed banks. We also show that neither before 2011 nor between 2011 and 2016 did exposed banks have significantly different levels of credit growth than non-exposed banks. Since the aggregate national and international variables remained the same for these two groups and we control for bank-level, time-variant, and time-invariant characteristics, we can say that the difference is purely due to their exposure to the iron and steel industry in 2011.

We also show that PVBs significantly decreased their exposure to the iron and steel industry in the 2000s, while PSB lending to these industries (as a proportion of their total lending) was almost twice that of the PVBs. This explains the relatively higher amount of NPAs declared by the PSBs. We also explore the possible sources of the decline in metal prices in the domestic market: the data suggest that this was predominantly driven by Chinese imports. With China being the world's largest steel producer as well as consumer, the decline in Chinese demand for steel in the 2010s led to sharp price cuts by Chinese sellers. This led to a severe decline in the profitability of Indian firms in the iron and steel industry, which then could not service their debts and defaulted on their debt obligation, thus creating NPAs in the banking sector. We also test the zombie lending argument by estimating a model of financial productivity and find that the data does not support this argument.

Although lending to industry entails a significant level of risk, it is vital for a country's growth prospects. Commodity price shocks contributed significantly to the problems in the banking sector in the late-1990s as well as in the 2010s, however it is hard to control or anticipate the commodity price cycle so as to mitigate adverse consequences, and hence appropriate policy actions are required. First, we must strengthen the commodity exchanges and associated futures and forward markets and non-financial firms should be encouraged to reduce their risks from commodity exposure by hedging these risks. This will help reduce risks associated with lending to commodity-sensitive sectors. Second, banking regulators need to reassess the norms on sectoral lending by banks. The concentration of bank lending portfolios in specific sectors can be risky, as the recent events related to commodity prices has illustrated. As lending to these sectors is critical for growth and the loan amounts tend to be large, banking regulators need to ensure the downside risk is cushioned. Banks can be advised to maintain safety margins or create a buffer, similar in nature to a counter-cyclical buffer, to safeguard themselves against negative commodity price risk.

Industrial lending is very different from retail lending. Assessing firms and making decisions on extending large loans require specialised skillsets. To propel the development process in the country, India set up specialised institutions known as development finance institutions (DFIs) after Independence, to cater to the financing needs of large infrastructure projects and for industrial loans. These projects were subject to higher risk and required government backing, so DFIs were especially important. They also ensured that negative spill overs from industrial lending did not affect financial intermediation in the economy. After the 1991 reforms, these institutions were converted into commercial banks. Initially, these new banks had significant exposure to commodity-sensitive industries such as iron and steel, but they gradually reduced their exposure in the 2000s, and PSBs took over this process. But in the 1990s the DFI-converted banks had faced issues emanating from their exposure to commodity-sensitive sectors. In the 2010s, public sector banks experienced a sharp rise in non-performing assets due to the commodity price crash. For continued growth, India needs to undertake large infrastructure projects but also ensure these don't hurt its financial sector. This brings us back to the question of setting up specialised institutions. The government is setting

up a new DFI, the National Bank for Financing Infrastructure and Development (NABFID). The results obtained in this paper suggest that appropriate pricing of risk by DFIs is critical to keeping them afloat. Our results are also consequential for the design of monetary policy. A financial crisis could emerge even during a stable inflation period: large movements in housing prices in the US led to a crisis which spread quickly to both sides of the Atlantic; similarly, a large swing in metal price could cause stress in the banking sector too. The popular inflation-targeting regime followed by the RBI allows scant consideration for the influence of sectoral deflation on policy, as it does not affect overall inflation being targeted by the central bank. But as we show in our paper, large sectoral deflation can have significant consequences and must receive due attention from the central bank.

References

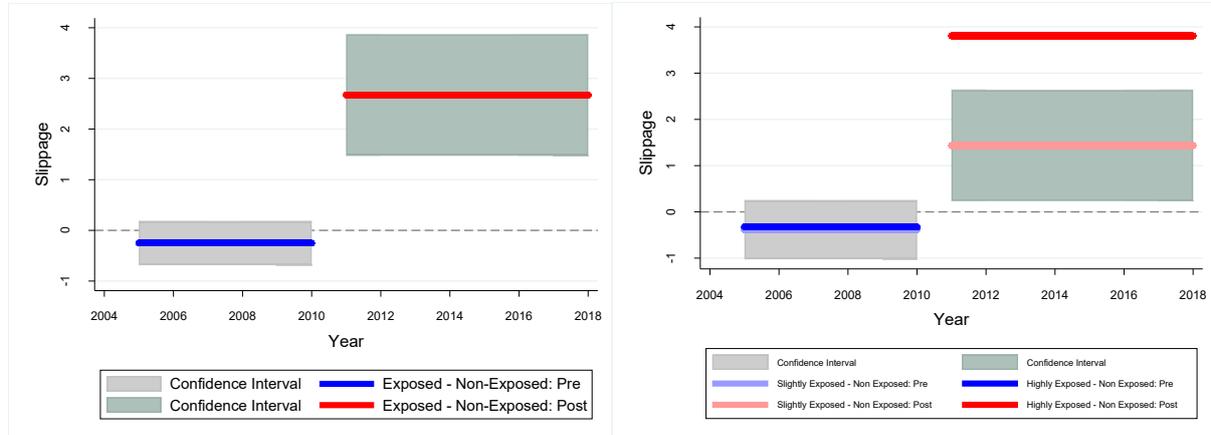
- Acharya, V., Das, A., Kulkarni, N., Mishra, P., & Prabhala, N.R. (2019). Anatomy of a banking panic. Mimeo.
- Agarwal, I., Dutttagupta, R., & Presbitero, A.F. (2020a). Commodity prices and bank lending. *Economic Inquiry*, 58(2), 953-979.
- Agarwal, R. (2023). The Past & Future of Indian Finance. M-RCBG Associate Working Paper Series.
- Agarwal, S., Correa, R., Morais, B., Roldan, J., & Ruiz Ortega, C. (2020b). Owe a bank millions, the bank has a problem: Credit concentration in bad times. FRB International Finance Discussion Paper, (1288).
- Ahamed, M.M., & Mallick, S.K. (2017a). House of restructured assets: How do they affect bank risk in an emerging market? *Journal of International Financial Markets, Institutions and Money*, 47, 1-14.
- Ahamed, M.M., & Mallick, S. (2017b). Does regulatory forbearance matter for bank stability? Evidence from creditors' perspective. *Journal of Financial Stability*, 28, 163-180.
- Banerjee, A.V., & Duflo, E. (2014). Do firms want to borrow more? Testing credit constraints using a directed lending program. *Review of Economic Studies*, 81(2), 572-607.
- Basu, D. (2015). Asymptotic bias of OLS in the presence of reverse causality. University of Massachusetts Amherst, Department of Economics. (No. 2015-18).
- Bazzi, S., & Blattman, C. (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics*, 6(4), 1-38.
- Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking Finance*, 30(11), 2931-2943.
- Blair, G., Christensen, D., & Rudkin, A. (2021). Do commodity price shocks cause armed conflict? A meta-analysis of natural experiments. *American Political Science Review*, 115(2), 709-716.
- Bruhn, M., & Love, I. (2014). The real impact of improved access to finance: Evidence from Mexico. *The Journal of Finance*, 69(3), 1347-1376.
- Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, 95(3), 780-795.
- Brunnermeier, M. K., Correia, S. A., Luck, S., Verner, E., & Zimmermann, T. (2023). The Debt-Inflation Channel of the German Hyperinflation (No. w31298). National Bureau of Economic Research.
- Chari, A., Jain, L., & Kulkarni, N. (2021). The unholy trinity: Regulatory forbearance, stressed banks and zombie firms. National Bureau of Economic Research (No. w28435).
- Chopra, Y., Subramanian, K., & Tantri, P.L. (2021). Bank cleanups, capitalization, and lending: Evidence from India. *The Review of Financial Studies*, 34(9), 4132- 4176.
- Choudhary, M.A., & Jain, A.K. (2021). Corporate stress and bank nonperforming loans: Evidence from Pakistan. *Journal of Banking Finance*, 133, 106234.
- Ciccone, A. (2018). International commodity prices and civil war outbreak: New evidence for Sub-Saharan Africa and beyond. CEPR Discussion Paper No. DP12625.
- Deaton, A., & Miller, R.I. (1995). International commodity prices, macroeconomic performance, and politics in Sub-Saharan Africa. *Princeton Studies in International Finance*, 79, October, 1-87.
- De V. Cavalcanti, T.V., Mohaddes, K., & Raissi, M. (2015). Commodity price volatility and the sources of growth. *Journal of Applied Econometrics*, 30(6), 857- 873.
- Dube, O., & Vargas, J.F. (2013). Commodity price shocks and civil conflict: Evidence from Colombia. *The Review of Economic Studies*, 80(4), 1384-1421.

- Eberhardt, M., & Presbitero, A.F. (2021). Commodity prices and banking crises. *Journal of International Economics*, 131, 103474.
- Faria-e-Castro, M., Paul, P., Sanchez, J. M. (2021). Evergreening (mimeo)
- Fernandez, A., Schmitt-Grohe, S., & Uribe, M. (2017). World shocks, world prices, and business cycles: An empirical investigation. *Journal of International Economics*, 108, S2-S14.
- Ferraro, D., & Peretto, P.F. (2018). Commodity prices and growth. *The Economic Journal*, 128(616), 3242-3265.
- Fisher, I. (1933). The debt-deflation theory of great depressions. *Econometrica: Journal of the Econometric Society*, 337-357.
- Gambacorta, L., & Mistrulli, P. E. (2004). Does bank capital affect lending behavior?. *Journal of Financial Intermediation*, 13(4), 436-457.
- Gurkaynak, R.S., Lee, S.S., & Karasoy-Can, G. (2019). Stock market's assessment of monetary policy transmission: The cash flow effect. CESifo Working Paper No. 7898. Retrieved from SSRN: <https://ssrn.com/abstract=3474205>
- John, N. (2016, May 08). Trophy Buy, Distress Sale. *Business Today*. Retrived from <https://www.businesstoday.in/magazine/cover-story/story/what-went-wrong-with-tata-steel-uk-operations-63609-2016-04-21>
- Kara, G., & Vojtech, C.M. (2020). Bank failures, capital buffers, and exposure to the housing market bubble. Finance and Economics Discussion Series 2017-115. Board of Governors of the Federal Reserve System (U.S.).
- Karlan, D., & Zinman, J. (2010). Expanding credit access: Using randomized supply decisions to estimate the impacts. *The Review of Financial Studies*, 23(1), 433- 464.
- Kumar, A., Mallick, S., & Sinha, A. (2021). Policy errors and business cycle fluctuations: Evidence from an emerging economy. *Journal of Economic Behavior & Organization*, 192, 176-198.
- Kumar, A., Mohan, R., Srinivasan, D., (2022). Commodity price shocks and non-performing assets in the Indian banking sector, CSEP Working Paper 38. New Delhi: Centre for Social and Economic Progress. Retrieved from <https://csep.org/working-paper/896538/>
- Meh, C. A., & Moran, K. (2010). The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics and Control*, 34(3), 555-576.
- Mohan, R., & Ray, P. (2017). Indian financial sector: Structure, trends and turns. IMF Working Paper. WP/17/7,1-35.
- Mohan, R., & Ray, P. (2019). Indian monetary policy in the time of inflation targeting and demonetization. *Asian Economic Policy Review*, 14(1), 67-92.
- Mohan, R., & Ray, P. (2022). The roller coaster ride of non-performing assets in Indian banking, CSEP Working Paper. New Delhi: Centre for Social and Economic Progress.
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 1417-1426.
- Rajan, R., & Ramcharan, R. (2015). The anatomy of a credit crisis: The boom and bust in farm land prices in the United States in the 1920s. *American Economic Review*, 105(4), 1439-77.
- Subramanian, A. (2019). India's GDP mis-estimation: Likelihood, magnitudes, mechanisms, and implications. CID Working Paper Series. Retrieved from <https://www.hks.harvard.edu/centers/cid/publications/faculty-working-papers/india-gdp-overestimate>
- Subramanian, A., & Felman, J. (2019). India's great slowdown: what happened? What's the way out? CID Working Paper Series. Retrieved from <https://dash.harvard.edu/handle/1/37366408>
- Whited, T.M. & Zhao, J. (2021). The misallocation of finance. *The Journal of Finance*, 76(5), 2359-2407.

Appendix

A. Robustness (Difference-in-Differences)

Figure A.1: Incremental Slippage of Banks exposed to Iron and Steel Sector (2005-2018)



(a) Incremental Slippage for Exposed Banks versus Non-Exposed

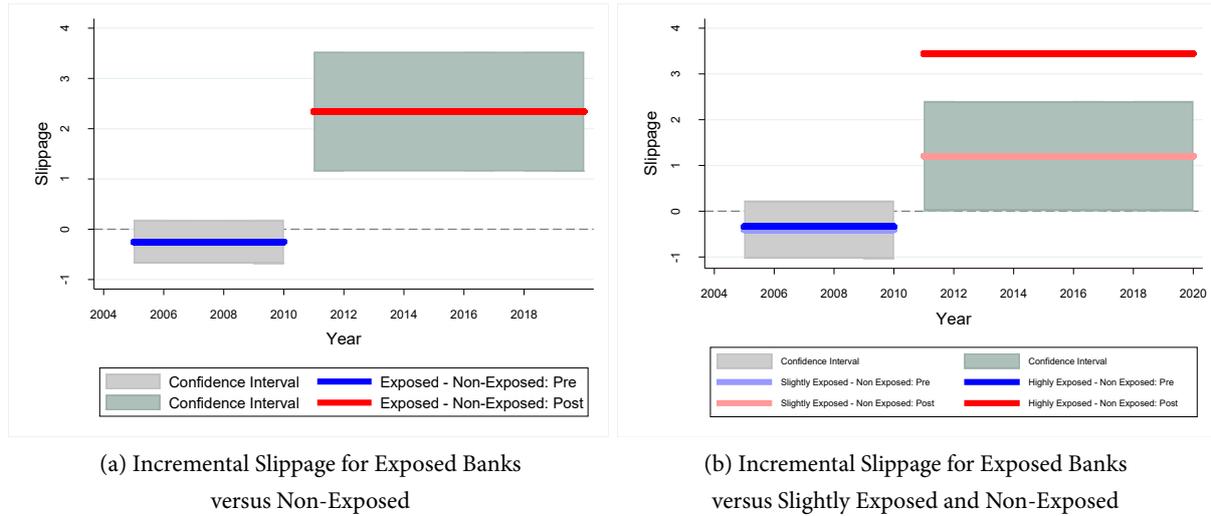
(b) Incremental Slippage for Exposed Banks versus Slightly Exposed and Non-Exposed

Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) is the difference between the NPAs of exposed and non-exposed banks after 2011 ($\beta_2 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel sector in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2018.

(b) represents β_{21} , β_{22} , β_{31} and β_{32} from $Slippage_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are the differences in the NPAs of $Exposed_1$ and $Exposed_2$ with non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference-in-differences of the NPAs of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 and before 2011. $Exposed_1$ are banks with an exposure to the iron and steel sector between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with an exposure to the iron and steel sector beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

Figure A.2: Incremental Slippage of Banks exposed to Iron and Steel Sector (2005-2020)

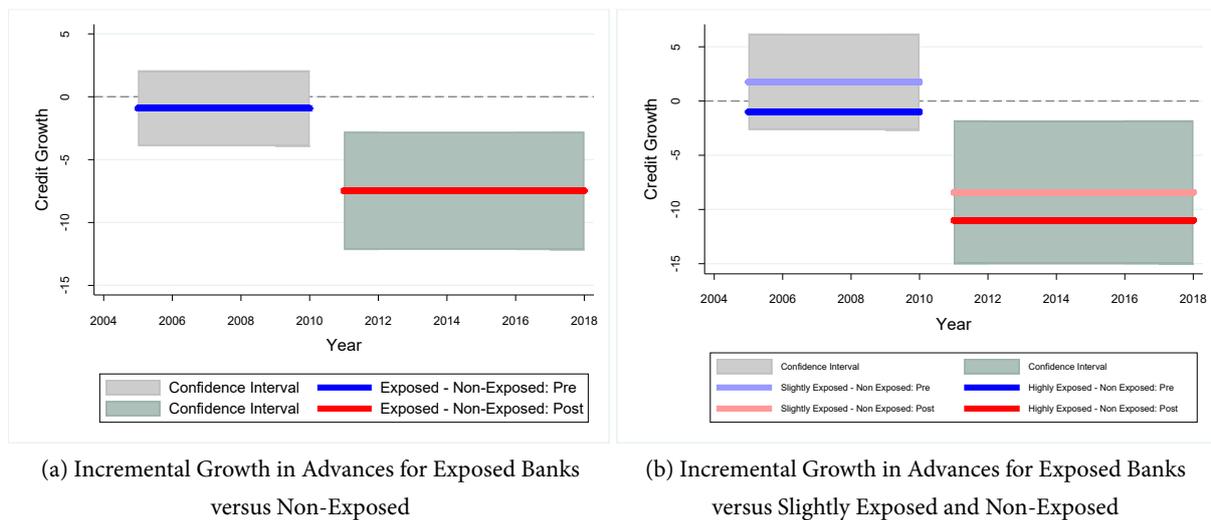


Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) gives the incremental difference between the NPAs of exposed and non-exposed banks after the metal price crash in 2011 ($\beta_1 + \beta_3$) relative to the difference before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel sector in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2020.

(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$ and β_{32} from $Slippage_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are the differences in NPAs of $Exposed_1$ and $Exposed_2$ with non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference-in-differences of NPAs of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 relative to the difference before 2011. $Exposed_1$ are banks with an exposure to the iron and steel sector between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with an exposure to the iron and steel sector beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI Bank Annual Reports

Figure A.3: Incremental Growth in Advances of Banks exposed to Iron and Steel Sector (2005-2018)

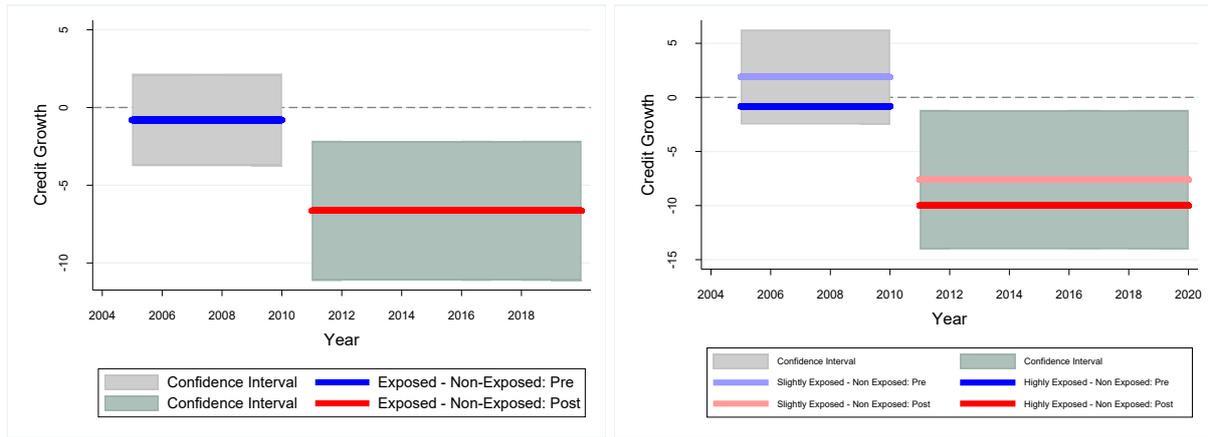


Notes: (a) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the growth in advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference-of-differences of the growth of advances of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2015.

(b) represents $\beta_{21}, \beta_{22}, \beta_{31}$ and β_{32} from $GAdvances_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are the differences of the growth of advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference in differences of the growth in advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 and before 2011. $Exposed_1$ are banks with an exposure to the iron and steel sector between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with an exposure to the iron and steel industry beyond the third quartile of the exposure distribution. $Slippage$ is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

Figure A.4: Incremental Growth in Advances of Banks exposed to Iron and Steel Sector (2005-2020)



(a) Incremental Growth in Advances for Exposed Banks versus Non-Exposed

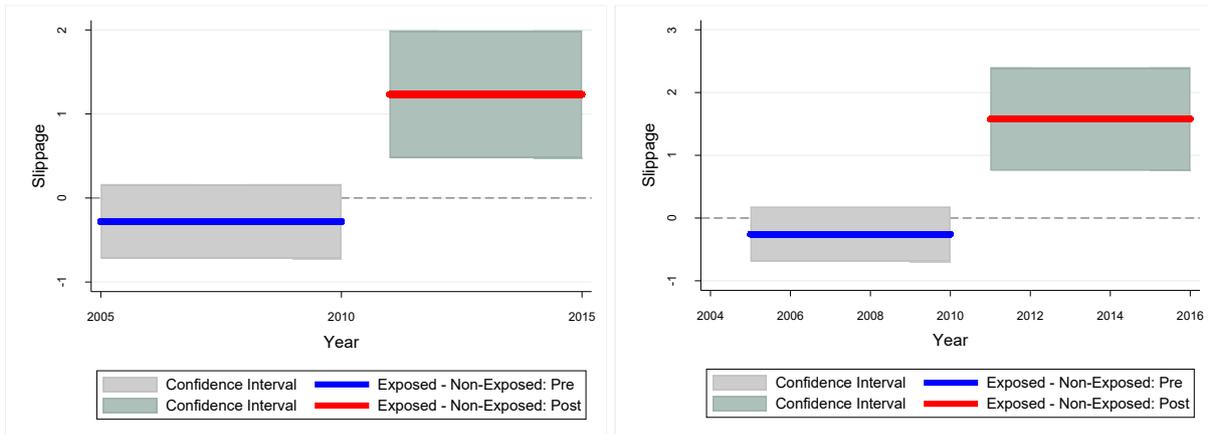
(b) Incremental Growth in Advances for Exposed Banks versus Slightly Exposed and Non-Exposed

Notes: (a) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between growth of advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference-of-differences in the growth of advances of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel sector in 2011. Post is a dummy which takes the value 1 for the years between 2011 and 2015.

(b) represents β_{21} , β_{22} , β_{31} and β_{32} from $GAdvances_{it} = \beta_0 + \beta_1 Post + \sum_{j=1}^2 \beta_{2j} Exposed_j + \sum_{j=1}^2 \beta_{3j} Exposed_j Post + \epsilon_{it}$. β_{21} and β_{22} (the light blue and blue lines) are differences of growth of advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks before 2011. β_{31} and β_{32} (the light red and red lines) are the difference-in-differences in the growth of advances of $Exposed_1$ and $Exposed_2$ with non-exposed banks after 2011 and before 2011. $Exposed_1$ are banks with exposure to the iron and steel industry between the median and third quartile of the exposure distribution. $Exposed_2$ denotes banks with an exposure to the iron and steel industry beyond the third quartile of the exposure distribution. Slippage is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

Figure A.5: Incremental Slippage of Banks exposed to Metal Sector (Iron & Steel and Metal Products)



(a) Incremental Growth in Advances for Exposed Banks (2005-15) (a) Treatment Year = 2015

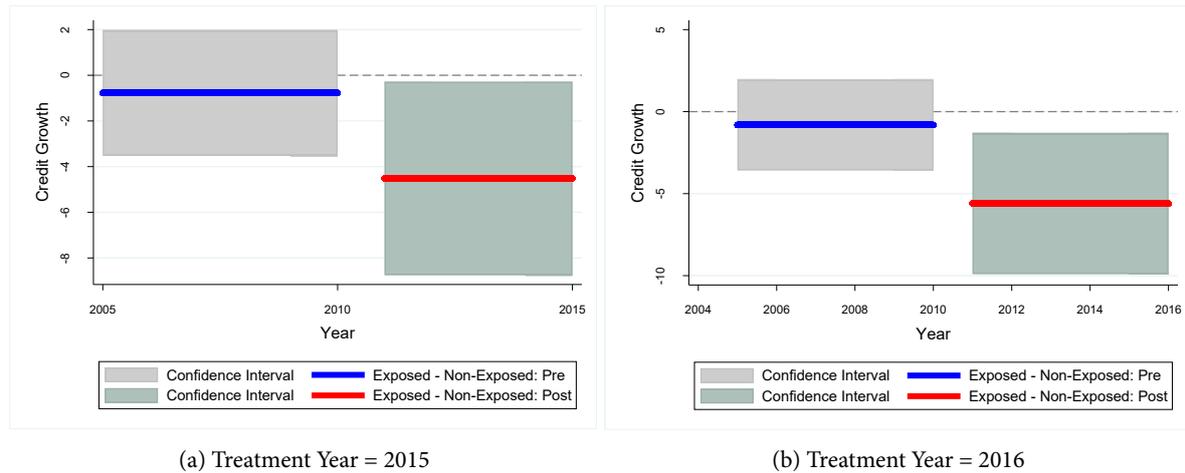
(b) Incremental Growth in Advances for Exposed Banks (2005-16) (b) Treatment Year = 2016

Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the NPAs of exposed and non-exposed banks before 2011. The red line (β_3) is the difference between the NPAs of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with the above mean exposure to the metal sector (iron and steel sector and metal products) in 2011. Post is a dummy which takes the value 1 for the years between 2011 and 2015.

Notes: (a) represents β_2 and β_3 from $Slippage_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. Blue line (β_2) is the difference between non-performing assets of exposed and non-exposed banks before 2011. Red line (β_3) is the difference between non-performing assets of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with the above mean exposure to the metal sector (iron and steel sector and metal products) in 2011. Post is a dummy which takes the value 1 for the years between 2011 and 2016. Slippage is the fresh addition to NPAs.

Source: RBI, Bank Annual Reports

Figure A.6: Incremental Growth in Advances of Banks exposed to Metal Sector



Notes: (a) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between growth of advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference-of-differences in the growth of advances of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with the above mean exposure to the metal sector (iron and steel sector and metal products) in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2015.

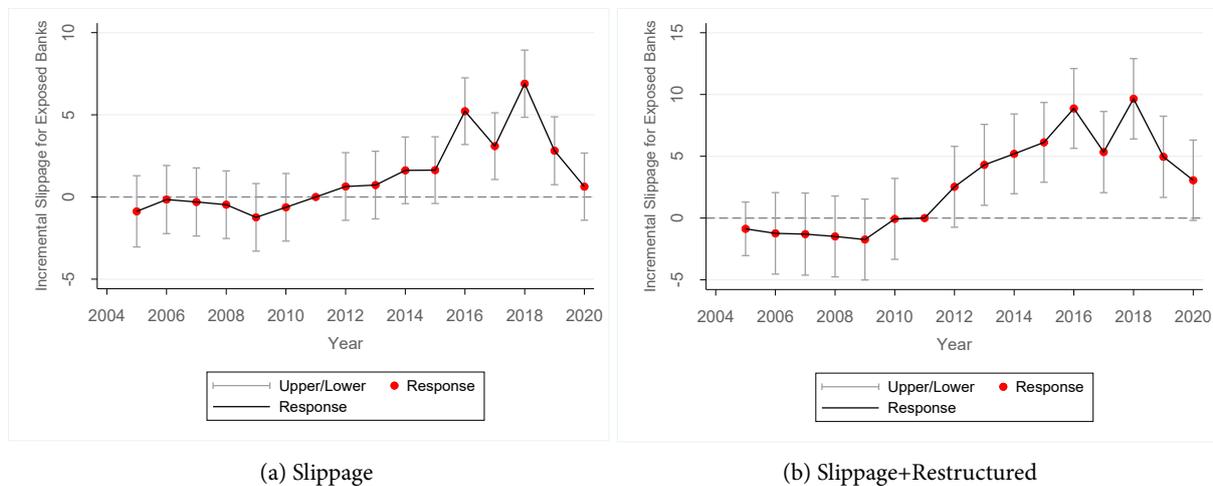
(b) represents β_2 and β_3 from $GAdvances_{it} = \beta_0 + \beta_1 Post + \beta_2 Exposed + \beta_3 \times (Post \times Exposed) + \epsilon_{it}$. The blue line (β_2) is the difference between the growth of advances of exposed and non-exposed banks before 2011. The red line (β_3) is the difference-of-differences in the growth of advances of exposed and non-exposed banks after 2011 ($\beta_1 + \beta_3$) and before 2011 (β_2). Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the metal sector (iron and steel sector and metal products) in 2011. $Post$ is a dummy which takes the value 1 for the years between 2011 and 2016.

Source: RBI, Bank Annual Reports

B: Evolution of NPAs in Banks Exposed to Iron and Steel Sector using Event Study

In this section, we present evidence using event study methodology from a major industry in the metal sector, iron and steel. We calculate the average exposure of banks to iron and steel sector in 2011, the year in which commodity prices started decreasing again after recovering from the 2008 crash. We classify banks as exposed and non-exposed, based on whether they have above- or below-mean exposure in the sector, respectively. We choose the year 2011 and not 2008 as we have data on a reasonable number of banks in both the exposed and non-exposed groups in that year. We estimate the following regression:

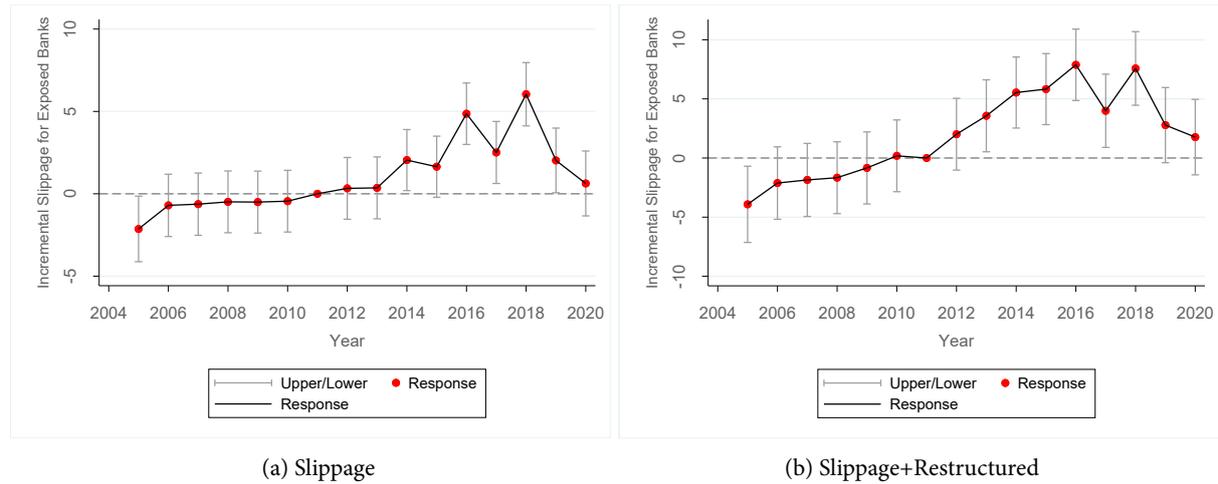
Figure B.1: Event Study Analysis: Evolution of Slippage and Slippage+Restructured



Notes: $\theta_{exposedy}$ is from $NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{exposedy} (Exposed \times D_y) + \epsilon_{it}$. D_y is the dummy variable for each year, y . Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. The dependent variable NPA_{it} is slippage and slippage+restructured. Slippage is the fresh additions to NPAs as a share of standard advances. Slippage+restructured is the sum of fresh additions to NPAs and the stock of restructured assets as a share of standard advances. Standard advance is the difference between gross advances and gross NPAs.

where D_y is the dummy variable for each year y . θ_i and θ_y are bank- and year-fixed effects, respectively. NPA_{it} is the slippage and slippage+restructured ratio as defined in the data section. The coefficient of interest is $\theta_{exposedy}$, which is the incremental slippage and slippage+restructured ratios for exposed banks. This empirical strategy has several benefits. First, since all the aggregate variables, such as domestic growth, the domestic interest rate, exchange rate, international growth, and international demand are the same for both groups of banks and their borrowers, these specifications are not likely to be adversely impacted by aggregate omitted variables.

Figure B.2: Event Study Analysis: Evolution of Slippage and Slippage+Restructured (with Bank-level controls)



Notes: $\theta_{exposedy}$ from $NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{exposedy} (Exposed \times D_y) + \theta' z_{it} + \epsilon_{it}$. D_y is the dummy variable for each year y . z_{it} contains the size and profit ratio for the bank. Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel sector in 2011. The dependent variable NPA is slippage and slippage+restructured. Slippage is the fresh additions to NPAs as a share of standard advances. Slippage+restructured is the sum of fresh additions to NPAs and stock of restructured assets as a share of standard advances. Standard advances is the difference between gross advances and gross NPAs.

Source: RBI, Bank Annual Reports

Bank-level variables can be important; therefore, we estimate an additional regression where we include bank-level controls such as size and profit ratios. Profit ratios are important for the declaration of NPAs, as less-profitable banks are less likely to hide these assets and resort to zombie lending, for fear of depleting their capital buffer.

$$NPA_{it} = \theta_i + \theta_y + \sum_y \theta_{exposedy} (Exposed \times D_y) + \theta' z_{it} + \epsilon_{it}$$

The above regressions are unlikely to suffer from confounding factors such as evergreening and zombie lending, as we categorise banks based on their 2011 share in the iron and steel industry. Figure B1 presents the coefficient of interest from the model without bank-level controls. As we can see, the exposed banks were not very different from the non-exposed banks in terms of fresh additions to their NPAs. In other words, there is no pre-trend in the data. We can say that the treatment and control groups satisfy the parallel trend assumption. From 2011 on, exposed banks experienced an increase in their NPAs. Once the forbearance period ended and the asset quality review had been completed, they declared significantly higher advances as NPAs. This is an important detail for the debate on Indian banking, as it shows that even if zombie lending took place during the period of regulatory forbearance, the initial reason for the surge in NPAs was exposure to the sector where prices had declined significantly.

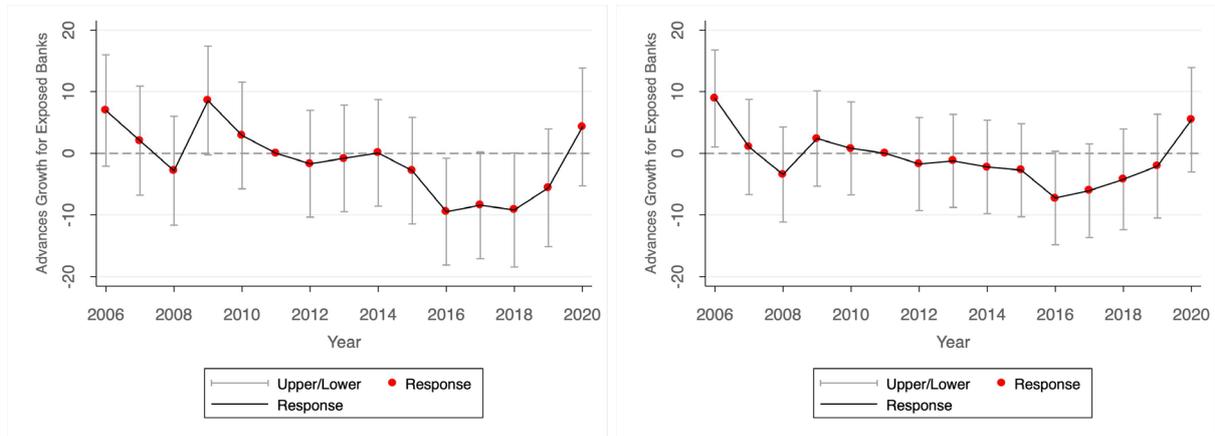
Figure B.2 presents the coefficient of interest from the model with bank-level controls, where we find similar results. It can be further argued that post-2011, exposed banks undertook reckless lending, which resulted in the accumulation of NPAs. To test, we estimate the following regression:

$$GADV_{it} = \theta_i + \theta_y + \sum_y \theta_{exposed_y} (Exposed \times D_y) + \theta' z_{it} + \epsilon_{it}$$

where $GADV_{it}$ is the growth rate of advances for bank i in year t . Figure B.3 presents the coefficient of interest from the model, with and without bank-level controls. There is no evidence that either before or after 2011, exposed banks experienced significantly higher credit growth than non-exposed banks. But once these banks declared their NPAs, their capital bases became depleted and they experienced a lower growth in advances (although it was not statistically different from that for non-exposed banks).

While we have presented evidence from one sector, several other sectors are also sensitive to commodity prices as we have shown earlier. Moreover, it is hard to obtain the precise extent of the effect of commodity prices on NPAs and credit growth using this framework. Therefore, in the next section, we design a general empirical framework to obtain the causal effect of commodity price changes on NPAs and the credit growth of banks.

Figure B.3: Event Study Analysis: Growth of Advances



(a) Growth of Advances

(b) Growth of Advances

Notes: $\theta_{exposed_y}$ from $GADV_{it} = \theta_i + \theta_y + \sum_y \theta_{exposed_y} (Exposed \times D_y) + \theta' z_{it} + \epsilon_{it}$. D_y is the dummy variable for each year y . Exposed banks ($Exposed = 1$) are banks with above-mean exposure to the iron and steel industry in 2011. The dependent variable $GADV_{it}$ is the growth in advances for bank i in year t . z_{it} contains the size and profit ratios for the bank. The left panel is without controls and right panel is with bank level controls, i.e., the size and profit ratios.

Source: RBI, Bank Annual Reports

C. Sources of the Price Decline in the Domestic Economy

The local/home country price P is related to the foreign price P^* and the exchange rate E based on the law of one price that is given by

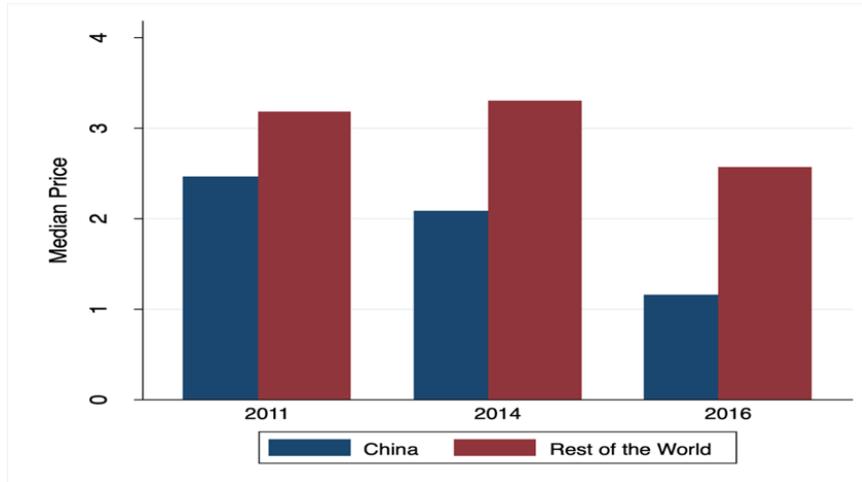
$$P = EP^*$$

which implies that

$$\%Change\ in\ P = \%Change\ in\ E + \%Change\ in\ P^*$$

Local prices may decrease for any or all of the following reasons: an exogenous appreciation of the domestic currency, an exogenous change in foreign prices, or exchange rate-induced changes in foreign prices. During 2011-14 the foreign prices of basic metals and metal articles (from the rest of the world excluding China) increased marginally, while they declined for metal products from China. But the sharp depreciation in India's exchange rate kept domestic prices from rising.

Figure C.1: Average unit price of imports (of iron and steel and articles of iron and steel) from China and the rest of the world excluding China



Notes: The graphs are based on matched 6-digit product code data obtained from Comtrade.

Source: World Bank.

During 2014-16, the median price of metal imports from both China and the rest of the world excluding China declined (figure C.1.). The decline was almost 50% for imports from China compared to a ~20% decline in imports from the rest of the world excluding China. The exchange rate did not depreciate enough to counter this large decline in dollar prices, hence prices in the domestic economy also declined. This is confirmed by trends in the wholesale price index of basic metals in the Indian market and the prices of some products such as billets (from the Prowess database shown in section 4).

A depreciation in the exchange rate increases the local price this will simultaneously make imports less competitive in the local market, which could then decrease their dollar price. The extent of this can be estimated by the pass-through regression. This allows us to also understand the shock-absorbing capacity of different kinds of sellers in the domestic market. We estimate a regression given by

$$\Delta \log Price_{it} = \theta_i + \Delta \log ExchangeRate_t + \theta_t + \beta t + \epsilon_{it}$$

Where i stands for the 6-digit product code and t for time. θ_i are the product fixed-effects, θ_t are the year fixed-effects, and β is the coefficient associated with a time trend. We estimate the above model for a matched sample for the period January 2011 to December 2019. The data is obtained from Comtrade (which gives the value and volume of imports) and WITS. We obtain the value and volume data for the rest of the world, and from this we obtain the unit value of imports from China and the rest of the world (excluding China).

As we can see in Table C.1. the exchange rate pass-through is incomplete for both China and the rest of the world. This implies that with depreciation the rupee price of imports increases, as the decline in the dollar price is not large enough to compensate for the depreciation, which is why exchange rate depreciation helped maintain higher domestic prices during 2011-14. Another interesting observation is that the pass-through for imports from China is higher than that for the rest of the world. This suggests that with depreciation Chinese exporters reduce their USD prices significantly more and hence have a larger shock-absorbing capacity.

Table: C.1 Exchange rate pass-through regression

	(1)	(2)
	Log Price China	Log Price Rest of the World
Rupee Dollar Exchange Rate	-0.674*** (-2.76)	-0.361* (-1.68)
Product Fixed-Effects	Yes	Yes
Year Fixed-Effects	Yes	Yes
Time Trend	Yes	Yes
Observations	19168	19168

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RBI, UN Comtrade, World Bank Pink Sheet

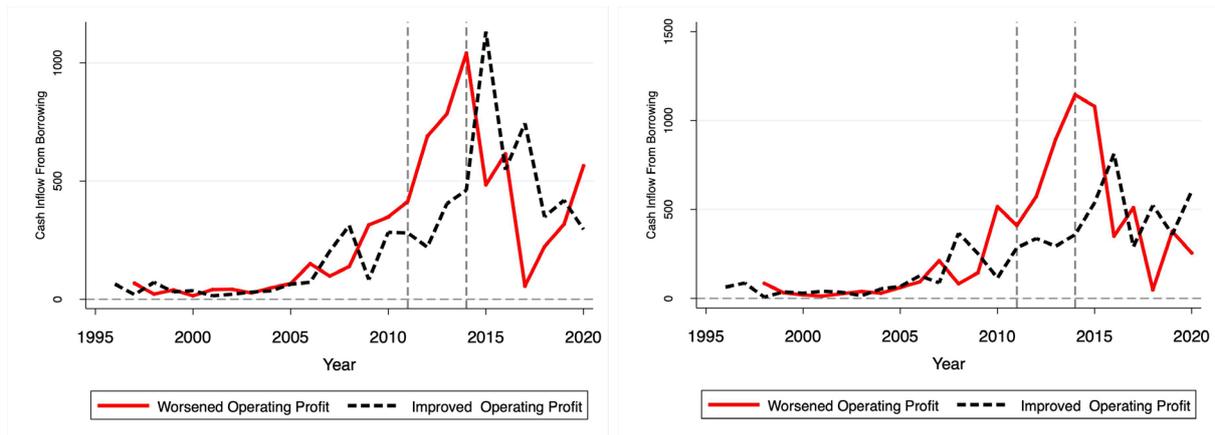
These results suggest that the decline in domestic prices after 2014 was predominantly a result of the very low prices of imports from China. They also suggest that producers from China have a higher ability to absorb shocks from the exchange rate shock, which could be driven by their higher productivity and lower marginal cost or by a greater extent of government assistance. If their marginal costs are lower than the rest of the world, it is quite obvious that P^* of products from China could have an important bearing on domestic prices P .

D. Zombie Lending vs. the Commodity Price Channel

Since a large proportion of the NPAs in banking were located in PSBs, bad management practices and zombie lending in these banks have been put forth as causal factors. The central point made in this paper is that PSBs accumulated higher NPAs because of their greater exposure to commodity prices, especially metals. In this section, we explore the possibility of zombie lending as an explanation for the build-up of NPAs as argued in Chari et al. (2021).

Figure D.1 indicates the cash flows from borrowings by firms with improving and worsening profits in the metals industry. Firms with improved operating profits in the left panel are those that experienced an increase in their operating profit ratio in time t compared to time $t-1$; other firms are categorised as firms with falling profits. Firms with improved operating profits in the right panel are those that experienced an increase in their operating profit ratios in time $t-1$ compared to time $t-2$; other firms are categorised as firms with declining profits. Clearly, for most of the period 2011-14, the large loans went to firms with worsening operating profit, but this could be because they genuinely needed assistance to handle the outcomes of the commodity price crash as argued by Agarwal et al. (2020b).

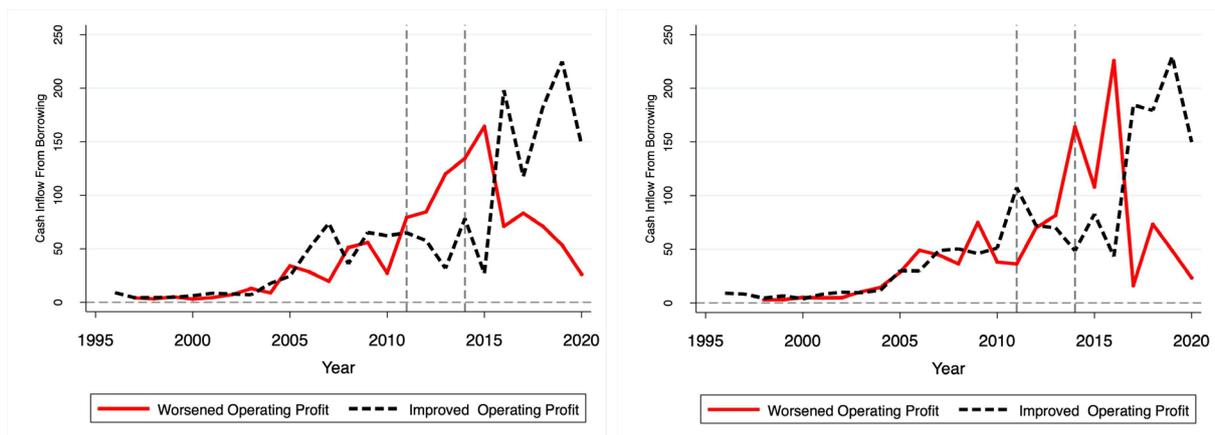
Figure D.1: Cash flow from borrowing by firms in the metals industry



Notes: We include all firms with the two-digit NIC codes 24 and 25 from the NIC (2008) classification. We exclude those with operating profits (as a % of sales) greater than 100 and lower than -100. Firms with improved operating profits in the left panel are those that experienced an increase in their operating profit ratios in time t compared to time $t-1$. Firms with improved operating profits in the right panel are those that experienced an increase in their operating profit ratios in time $t-1$ over time $t-2$.

Source: CMIE Prowess, IBBI

Figure D.2: Cash flow from borrowings by firms in the drugs and pharmaceutical industry



Notes: We include all firms with the two-digit NIC code 21 from the NIC (2008) classification. We exclude those with operating profits (as a % of sales) greater than 100 and lower than -100. Firms with improved operating profits in the left panel are those that experienced an increase in their operating profit ratios in time t compared to time $t-1$. Firms with improved operating profits in the right panel are those that experienced an increase in their operating profit ratios in time $t-1$ over time $t-2$.

Source: CMIE Prowess, IBBI

Changes in operating profits in time $t-1$ compared to time $t-2$ are clearly evident to bankers, hence this lending pattern could be construed to be zombie lending. But we argue that is not the case, given that loans are extended based on a large amount of information privately available to banks, which would never be available to econometricians to argue for a case of zombie lending in the true sense. This is confirmed by Figure D.2 which compares the cash flow from borrowings by firms in the drugs and pharmaceutical industry which experience improving profits versus firms with worsening profits. We find a similar pattern – of a larger proportion of loans to firms with worsening profits. Hence, we argue that analysing the flow of loans based on publicly available information about a bank is not sufficient to make a case for bad practices, as lending decisions are based on a large amount of private information.

To explore the zombie lending channel in further detail, we construct a measure of financial productivity as in Whited and Zhao (2021):

$$F_{ist} = A_{ist} \left(\alpha D_{ist}^{\frac{\gamma_s-1}{\gamma_s}} + (1-\alpha) E_{ist}^{\frac{\gamma_s-1}{\gamma_s}} \right)^{\frac{\gamma_s}{\gamma_s-1}}$$

where F_{ist} is the measure of financial output such as operating profit, D_{ist} is total debt, E_{ist} is total equity, γ_s is the elasticity of substitution, and α is the share of debt in the capital. The first-order approximation of the above equation can be written as

$$\log(F_{ist}) = \alpha + u_{ist} + \alpha \log D_{ist} + (1-\alpha) \log E_{ist} + \frac{1}{2} \alpha (1-\alpha) (\gamma_s - 1) [\log D_{ist} - \log E_{ist}]^2$$

where A_{ist} is productivity of the total financial capital and is written as the sum of the common component α and the idiosyncratic component u_{ist} . A higher A_{ist} implies that a firm is able to generate greater financial benefits from a given level of total financial capital. For lenders, A_{ist} constitutes the most relevant publicly available information. We regress the cash flow from borrowing (CFB_{it}) on financial productivity (A_{ist}), size ($\log Sales$), and total fixed assets $\log FixedAssets$. Total fixed assets could be important for borrowing especially in the event of an assets-based borrowing constraint as argued in Kumar et al. (2021).

$$CFB_{ist} = \theta_i + \theta_t + \beta_1 \text{Lag} A_{ist} + \beta_2 \text{LogSales}_{ist} + \beta_3 \text{LogFixedAssets}_{ist} + e_{ist}$$

where θ_i and θ_t are firm- and year-fixed effects, respectively, and s represents the sector. We consider two sectors – metals and drugs and pharmaceutical. We include the lag of financial productivity as this is observed by lenders while deciding on a loan. Tables D.1 and D.2 present the results for the metals sector and the drugs and pharmaceutical sector, respectively. In the metal sector the sign of the coefficient associated with financial productivity β_1 is positive for the overall sample and negative in the more-recent sample, but is not significant in either case. The log of sales has a positive effect on cash flows from borrowings, and is statistically significant in the pre-commodity price crash (2011) period. The coefficient associated with the log of fixed assets is not significant, but becomes positive in the more-recent sample. Since the lag productivity is observed by the lender, giving loans to firms with decreasing financial profitability could be construed as zombie lending. The coefficient of lag productivity post-2011 is negative, hence one could argue for the presence of zombie lending to some extent (as the coefficient changed from positive to negative). But similar negative coefficients are found for all time periods in the drugs and pharmaceuticals sector (table D.2), with no banking NPAs related to that industry.

Table: D.1 Cash flow from borrowing and financial productivity: Metals sector

	(1)	(2)	(3)
	Cash Flow from Borrowing	Cash Flow from Borrowing	Cash Flow from Borrowing
Lag Productivity	-2.352 (-1.46)	0.937 (1.35)	-3.782 (-0.94)
Log Sales	2.534 (1.55)	0.595** (2.82)	2.808 (1.01)
Log Fixed Assets	1.752 (1.43)	-0.146 (-0.54)	1.518 (0.86)
R2	0.044	0.032	0.019
N	6599	3521	3078
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Notes: *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively. Column (1) refers to the time period 1996-2020; column (2) refers to 1996-2011; and column (3) to the time period 2012-20. We take all firms with two-digit NIC codes 24 and 25 from the NIC (2008) classification, and exclude those with operating profits (as a % of sales) that are higher than 100 and below -100.

Table: D.2 Cash flow from borrowing and financial productivity: Drugs and pharmaceutical industry

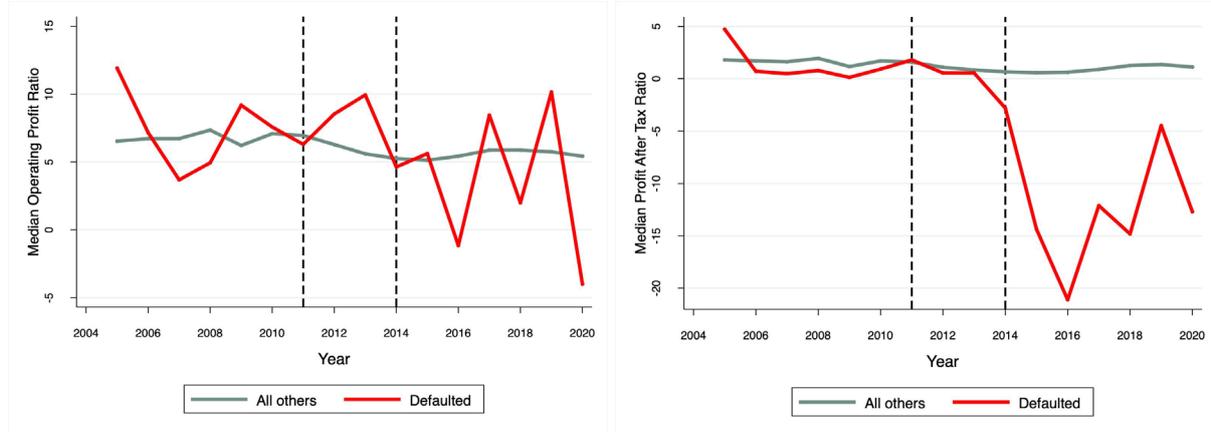
	(1)	(2)	(3)
	Cash Flow from Borrowing	Cash Flow from Borrowing	Cash Flow from Borrowing
Lag Productivity	-1.248 (-1.24)	-0.479 (-1.96)	-0.0336 (-0.06)
Log Sales	0.491 (1.38)	0.148* (2.27)	1.461 (0.98)
Log Fixed Assets	0.990* (2.49)	0.267*** (3.50)	2.211 (1.87)
R2	0.051	0.096	0.038
N	3003	1680	1323
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Notes: *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively. Column (1) refers to the time period 1996-2020; column (2) refers to 1996-2011; and column (3) to the time period 2012-20. We include all firms with the two-digit NIC code 21 from the NIC (2008) classification, and exclude those with operating profits (as a % of sales) higher than 100 and lower than -100.

These results make it clear that the argument of zombie lending based on accounting/observed data cannot be a valid explanation for the banking crisis. Zombie lending cannot provide a consistent explanation for the build-up of NPAs, unlike the commodity price channel explored in this paper, because the commonly used criteria for zombie lending would imply zombie lending in sectors that did not have problems with NPAs. This erroneous implication based on the zombie-lending argument arises due to a lack of clarity about banks' lending decisions: banks base these decisions on a large amount of private information which is not available to econometricians.

E. Profitability and Share of Defaulting Firms in Total Assets and Total Sales in the Metals Sector

Figure: E.1: Profitability ratios of defaulting firms relative to all others.



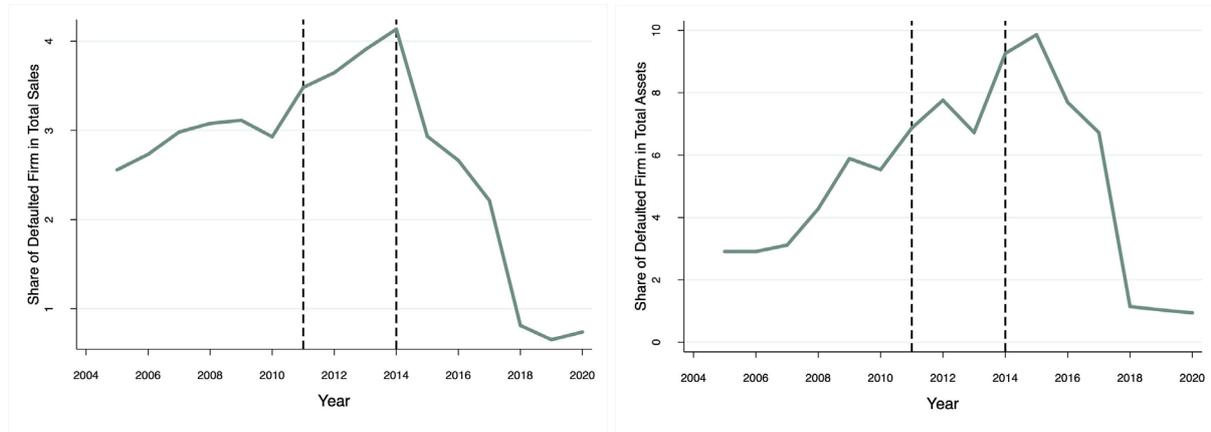
(a) Operating Profit Ratio

(b) Net Profit Ratio

Note: We exclude firms with operating and net profits ratios over 100% and less than -100%. For each group we calculate the year-wise mean of the ratios. The cash flow from borrowings is the net cash flow from borrowing from all the sources and is denoted in billion rupees.

Source: CMIE Prowess and IBBI

Figure: E.2 Share of Defaulted firms in Sales and Total Assets



(a) Share in Sales

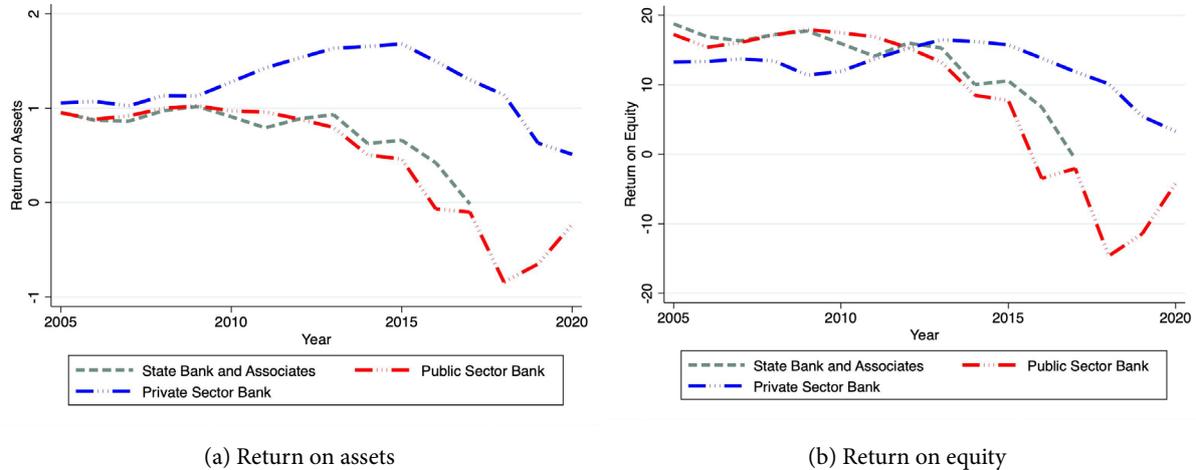
(b) Share in Total Assets

Note: We exclude firms with operating and net profits ratios over 100% and less than -100%. For each group we calculate the year-wise mean of the ratios. The cash flow from borrowings is the net cash flow from borrowing from all the sources and is denoted in billion rupees.

Source: CMIE Prowess and IBBI

F. Performance of Public Sector Banks Versus Private Banks

Figure F.1: Return on Assets and Equity across Bank Groups



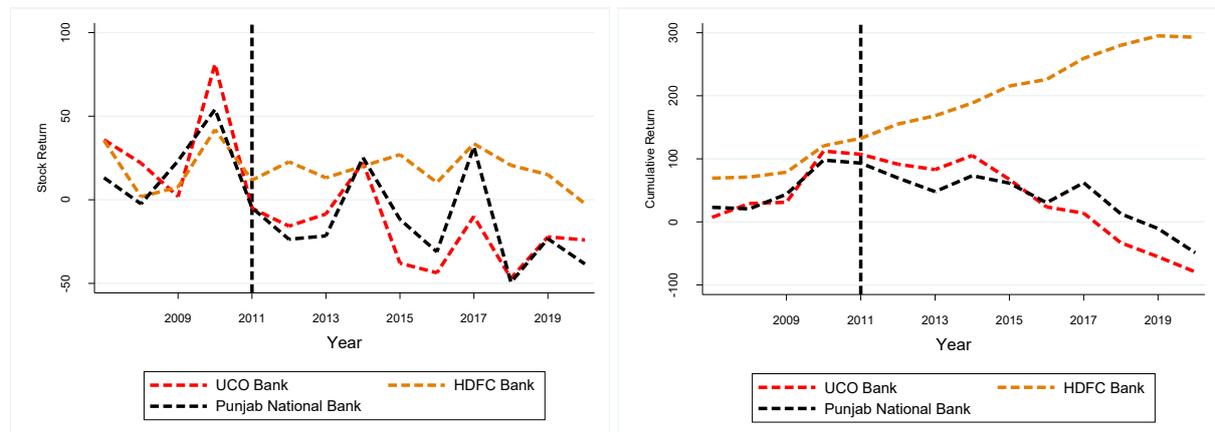
Note: We include all banks in the RBI database and their classifications. Private banks do not include foreign banks.

Source: RBI

The deterioration in the financial performance of PSBs in the 2010s has been linked to governance issues stemming from their public ownership, without any reasonable evidence to support this claim. As we can see from Figure F.1, the return on equity for PSBs was higher than for private banks (PVBs) till 2012, but fell lower PVBs after 2012. This is because of their higher exposure to commodity-sensitive sectors as we will show in the next section.

Even the return on assets was similar for PSBs and PVBs before the commodity price crash of 2011. The divergence started in 2010, and was likely driven by the delayed effect of the commodity price crash in 2008-09 and intensified after the 2011 price crash. Hence, there is little evidence to link ownership with performance, but there is significant evidence to explain the divergence in performance based on sectoral exposure of the two banking groups, which we will do in the next section.

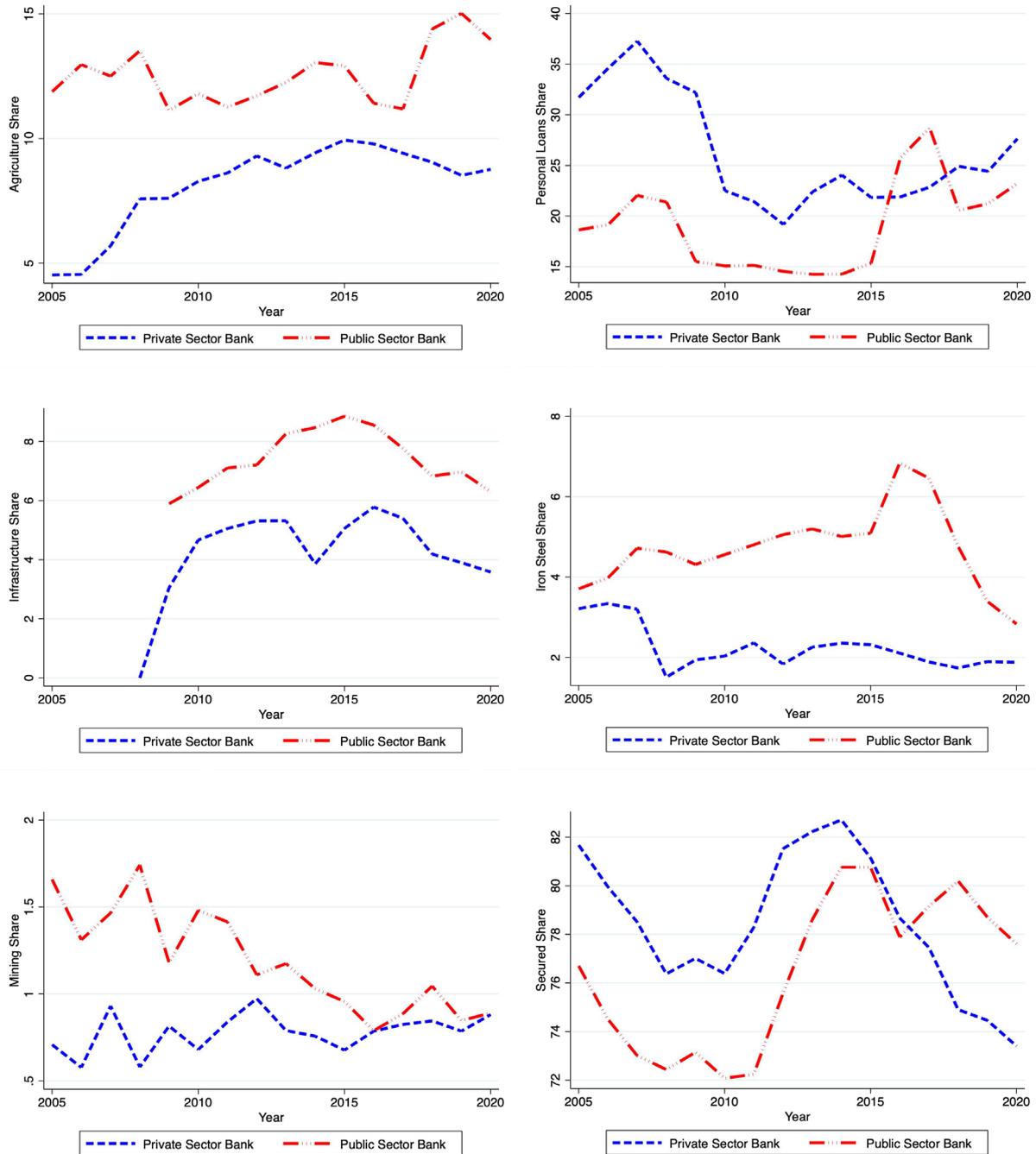
Figure F.2: Evidence from the Stock Market



Return on Stocks (figure F.2.) shows how the trend of stock returns for all three banks mentioned above very similar before 2011. The cumulative return for HDFC, PNB and UCO from 2005-2010 was almost the same. However, there is a clear divergence in the returns for HDFC and the other two banks thereafter, reiterating our point on the decline in commodity prices affecting banks exposed to the commodity sensitive sector.

G. Sectoral Lending of Public and Private Banks

Figure: G.1: Sectoral lending across Bank Groups



Note: The figures include all banks in the RBI database and their classifications. Private banks do not include foreign banks.

Source: RBI

The comparison between public and private banks has largely pointed to adverse governance issues in PSBs causing disproportionately higher NPAs. Very little attention has been paid to the stark differences in their business models in terms of risk-taking, and the effect on the relative performance of the two groups of banks. During 2005-10, private sector banks (PVBs) had a significantly higher share of retail loans (to total loans) compared to PSBs. These are loans to individuals and households; given their relatively higher interest yields and relatively lower risk, this aided the growth of PVBs

in the early 2000s. The difference in the share of retail lending between PVBs and PSBs was more than 10% at its peak. During 2016-17 when NPAs rose in PSBs due to the delayed effect of the commodity price crash, their share of retail lending rose, surpassing that of PVBs, but eventually fell below. PSBs had a significantly higher share of lending to relatively risky sectors, such as iron and steel, which are the focus of this paper. Interestingly, from 2008 on PVBs reduced their share of loans to the iron and steel industry while PSBs increased their share. As we argue in this paper, the largest amount of defaults was recorded in the metals sector, including iron and steel, which is why the metal price crash post-2014 disproportionately affected PSBs.

In other risky sectors such as infrastructure, mining, and agriculture, too, PSBs had a significantly higher share of lending than PVBs. Hence, we can argue that the differences in the business models of these two groups of banks led to significantly different impacts of exogenous shocks, such as the commodity price crash, which is what happened in the Indian banking sector after the 2011 price crash.

When we turn to the possibility of zombie lending, the increasing proportion of secured loans in PSB portfolios after 2011 is incompatible with the argument of zombie lending. Zombie lending by PSBs should have been followed by a decreased share of secured loans by them. Also, we see that in recent years the secured lending share of PSBs is higher than that of PVBs.

H. Exposure and Non-Performing Assets in Public and New Private Banks, 1996-97 to 2003-04

Table H.1: Gross NPAs (as a % of gross advances)

Fiscal Year	Scheduled Commercial Banks (SCBs)	Public Sector Banks (PSBs)	New Private Banks (NPBs)
1996-97	15.7	17.8	2.6
1997-98	14.4	16.0	3.5
1998-99	14.7	15.9	6.2
1999-00	12.7	14.0	4.1
2000-01	11.4	12.4	5.1
2001-02	10.4	11.1	8.9
2002-03	8.8	9.4	7.6
2003-04	7.2	7.8	5.0

Source: Reserve Bank of India

In the mid-1990s gross NPAs (as a % of gross advances) in the scheduled commercial banks (SCBs) peaked at 15.7%, with the bulk of these being concentrated in the PSBs (17.8% versus 2.6% in new private banks [NPBs]). The commodity price fall of the late-1990s, however, altered this pattern. Between 1999-00 and 2001-02, while NPAs in PSBs decreased to 11.1% (from 14%), they increased to 8.9% (from 4.1%) for NPBs (Table H.1).

Table H.2: Exposure and gross NPAs of ICICI Bank (1999-2001)

	Exposure (as a % of Total)			GNPA (as a % of total NPA)		
	1999	2000	2010	1999	2000	2010
Metal & Metal Products	13.5	13	4.6	17.2	17.1	1.5
Textiles	9.5	8.7	1.0	21.2	23	2.0
Retail	0.1	0.7	44.4			

Source: ICICI Annual Report 2001

Higher exposure in commodity sectors and the commodity price crash explain the poor performance of NPBs in the late-1990s. The exposure and NPAs of ICICI Bank, which was one of the largest NPBs, is given in Table H.2. Apart from infrastructure, in 1999-2001 ICICI's lending portfolio was heavily concentrated in commodity-sensitive sectors such as metal and metal products, and textiles. Retail lending was very low at just 0.1% (as a % of total exposure) in 1999, increasing to 2.6% in 2001. These commodity sectors accounted for most of their NPAs during the commodity price crash in the late-1990s: metals and textiles together contributed to approximately half their NPA burden in 2001. The commodity exposure of NPBs such as ICICI was likely driven by their past legacy as development finance institutions (DFIs).

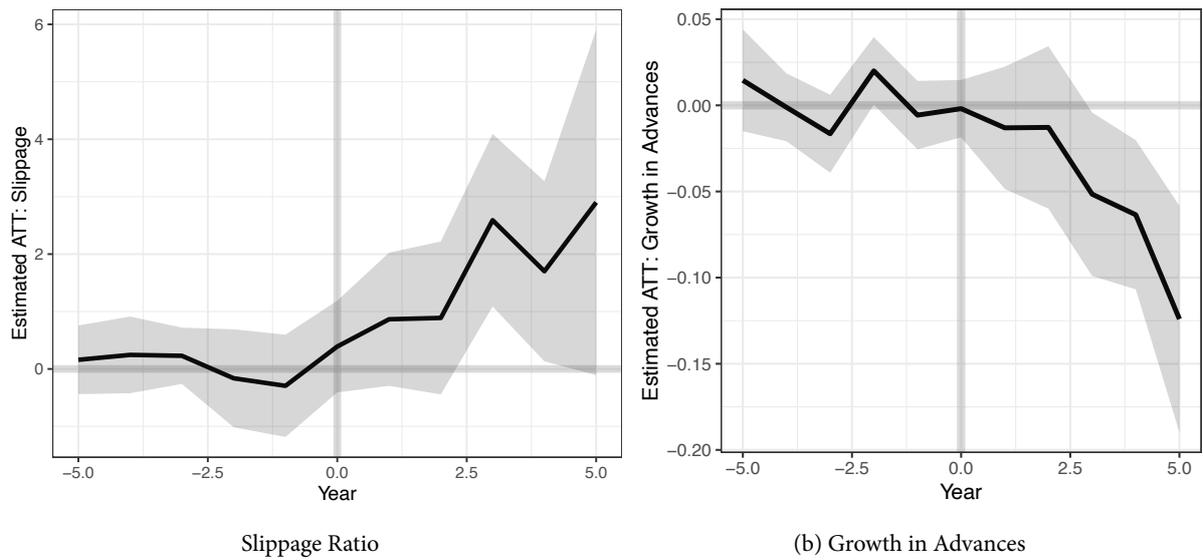
In the last two decades, banks like ICICI have changed their business model, focussing heavily on retail lending, vis-a-vis the PSBs, which are still doing the heavy lifting in lending to industry. This has become a major difference in the banking models of the two groups. Lending to industry is critical for development of the economy, but commodity shocks (like those in the late-1990s) have deterred PVBs from extending their exposure to these sectors; if this course were to be followed by PSBs, industry would be starved for credit sources. Therefore, it is very important to formulate policy that takes into consideration such exogenous shocks, if we are to safeguard the future development prospects of the country.

I. Robustness: Effects of Commodity Prices Exposure on Slippage and Credit Growth Using Generalised Synthetic Control

The identification of control group in our difference-in-differences regression has been made based on the banks' proportion of exposure to a sector (iron & steel) in 2011. All banks with below mean exposure to the metal sector are considered to be the control group. One may argue about the arbitrariness of this threshold. For robustness, we perform a regression using the generalised synthetic control method (GSCM). By creating a weighted combination of units, the synthetic control approach creates a control group that simulates what the treated group would have experienced in the absence of treatment and estimates treatment effects.

Figure G.1 (a) shows the average treatment effect on the treated (ATT). It compares the observed slippage ratios of the treated group to their counterfactual. From the figure it is clear that in the years before the fall in commodity prices, the slippage of all the banks, on average, was similar. Post the treatment, in line with our results in the paper, we notice an increase in the slippage of banks which are highly exposed to the iron and steel sector. The difference becomes significant in 2.5 years after the treatment, when banks have tried restructuring or other measures, but eventually need to declare the loans as NPAs. We use two-way fixed effects and control for bank and year fixed effects.

Figure H.1 Average Treatment Effect (ATT) on Banks Exposed to Iron & Steel Sector



Note: Treated group includes banks with above mean exposure to the iron and steel sector. The generalized synthetic control method used here is based on parametric inferential method for Slippage and jackknife for Growth in Advances with two-way fixed effects.

Source: Author's own calculations

As the slippage ratios of exposed banks increase, their Growth in Advances (figure G.1 (b)) start to decline after the commodity price fall. This shows our results in the paper are robust and independent of the threshold on exposure of banks.

Independence | Integrity | Impact

Centre for Social and Economic Progress

6, Dr Jose P. Rizal Marg, Chanakyapuri, New Delhi - 110021, India



@CSEP_Org



@csepresearch



www.csep.org