Do recessions induce the Schumpeterian creative destruction? Micro-evidence from India

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ABSTRACT

According to the Schumpeterian cleansing hypothesis, economic downturns force inefficient firms off the market, thereby freeing resources that can be allocated to more efficient firms. Friction may inhibit this efficient allocation of resources in a developing country like India. We analyse whether the view that recessions have a silver lining by fostering efficient resource allocation holds true by utilising the comprehensive micro-level data for publicly traded firms, including both industrial and service firms, from 1988 to 2020. We find that reallocation is generally efficiency-enhancing, i.e., credit flows from low-productive firms to high-productive firms, and *normal* economic downturns induce this efficiency-enhancing reallocation. Our results suggest that economic downturns induce efficiency-enhancing reallocation in manufacturing but not in services. However, we find no evidence of a cleansing effect during the Asian and a modest cleaning effect during the global financial crises. We do observe that reallocation was efficiency reducing during India's financial crisis, which contradicts the cleansing effect. Our findings show that financial constraints on productive firms could be one of the potential explanations for the lack of a cleansing effect.

Keywords: Credit reallocation, Productivity, Cleansing effect, Severe economic downturns.

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1. Introduction

The efficient allocation of resources for productivity growth has become a pressing research issue, particularly in developing economies. According to study by (Hsieh & Klenow, 2007), India would gain 40–60% in productivity if it had the same resource allocation efficiency as the United States. There is ample evidence which suggests that the availability of finance matters for firms' performance. The growing strand of literature provides evidence of cross-sectional heterogeneity in firm level behaviour, even within narrowly defined sectors or industries (Ahn, 2005; Caves, 1998; Davis & Haltiwanger, 1990; Doms & Bartelsman, 2000; Roberts & Tybout, 1997). Therefore, firms can have differential access to credit even within their size, sectors, and region and be exposed to persistent idiosyncratic factors affecting their borrowing ability. Moreover, the allocation of credit can be hindered by the friction present in the credit market. As empirical evidence demonstrates, the allocation of credit affects a firm's performance; hence, the flow of credit to an unproductive firm, which might result from the firms' heterogeneity and frictions in the credit market, can affect aggregate productivity and impair economic growth (Caballero et al., 2008; Caballero & Hammour, 2005; Eisfeldt & Rampini, 2006; Ana Maria Herrera et al., 2011; Kulkarni, 2021).

The pervasive empirical finding is that massive reallocation of resources exists for all countries, providing the empirical evidence of creative destruction[3] (Bartelsman et al., 2004). The extant literature in the context of credit markets also shows that significant amounts of gross credit flows co-exist at each stage of the business cycle, even within narrowly defined sectors, implying that some firms increase their debt while others decrease it (Ana Maria Herrera et al., 2011; Junghwan Hyun & Minetti, 2019; Sakai & Uesug, 2020). Empirical research shows that

[3] Schumpeter's process of creative destruction, where the new displaces the old; new firms enter, and the incumbent firms expand to produce the newly innovated products and services. Through this dynamic competition, physical (capital, labor) and financial inputs are moved from firms that aren't productive and are going out of business to firms that are more productive and growing quickly. This leads to increased efficiency, higher productivity, and growth.

the processes of creative destruction and productivity growth are closely intertwined, and this productivity-enhancing reallocation intensifies during economic downturns.

The notion that recessions might have a cleaning effect by inducing the reallocation of resources from lower to higher productivity uses dates at least to Schumpeter (1939, 1942). According to his perspective, recessions force inefficient firms off the market, thereby releasing resources that can be allocated to more efficient firms. Since then, a great deal of attention has been paid to this hypothesis, but the fundamental question of whether recessions genuinely have this silver lining is still being contested. (Caballero & Hammour, 1991b) postulated in their model that recessions have a cleansing effect, which was later contradicted by (Barlevy, 2002, 2003; Caballero et al., 2008; Caballero & Hammour, 2005; Ouyang, 2005) finding that in the presence of friction, such as credit market friction, the cleansing effect may reverse, i.e., resources may drive from more productive to less productive, potentially scarring or sullying effect. There is evidence that recessions clean up the economy (Davis & Haltiwanger, 1990; Foster et al., 2001; Ramey & Shapiro, 1998), but at the same time, some studies suggest that severe economic downturns may not be able to reinforce the productivity enhancing reallocation (Foster et al., 2016; Hallward-Driemeier & Rijkers, 2013; Sakai & Uesug, 2020). (Bartelsman et al., 2018; Foster et al., 2016) suggest that the nature of the economic downturn may also play a role in whether recessions have productivity-enhancing or productivity-reducing reallocation.

Therefore, shedding light on how these microeconomic fluctuations (reallocation) and the macroeconomic fluctuations (business cycle) are related has important policy implications. If recessions are cleansing, counter-cyclical policies enacted to stabilise the business cycle may impede long-term economic growth; if the opposite is true, counter-cyclical policies would improve both short- and long-term prospects.

The important shortcoming of the aforementioned studies is that they primarily focus on the labour market. This study fills a void in the literature by providing novel evidence on the cleansing effects of recessions in the context of the credit market, for which evidence was previously lacking. Few studies attempt to examine the relationship between productivity and credit reallocation. (Ana María Herrera et al., 2014; Junghwan Hyun & Minetti, 2019) examine the relationship between credit reallocation and a proxy index for the efficiency of investment allocation that is distinct from total factor productivity (TFP). (Sakai & Uesug, 2020) investigate the extent and efficiency of credit reallocation for Japan and find that reallocation is efficiency-enhancing in general, but during the lost-decade it was efficiency-reducing. Though this study is closely related to ours, we contribute to the literature in the following way. *First*, to our knowledge, we are the first to examine the linkages between credit reallocation and productivity not only for all publicly traded firms but also at the sectoral level (manufacturing and services). The two industries have extremely different characteristics. Consequently, if crises have significantly different effects on the two sectors, research that solely uses data from the manufacturing sector may offer a skewed picture of the effect of crises on aggregate productivity dynamics. *Second*, our sample allows us to study the cleansing effect of not only the short-term economic downturns but also the crises such as the Asian financial crisis, global financial crisis, and Indian financial crisis, all of which had distinct underlying causes and repercussions. *Finally,* despite having many characteristics in common between Korea and India's financial sector, both economies can still not be compared as the former is considered a developed economy. At the same time, the latter is still a developing economy. Therefore, it would be interesting to see whether similar results hold for India as well, with a different institutional background.

The study's focus on India to test the cleansing hypothesis is intriguing for the following reasons: First, India's financial system is bank-dominated and compared to many developed and emerging countries, India relies heavily on debt financing. The second interesting aspect is our unique firm-level database and the period covered. In our sample, in addition to normal economic downturns, it also includes three crisis periods, which allows us to study how efficiency-enhancing reallocation changes during severe economic downturns. For instance, to mitigate the effects of the global financial crisis on the economy, a policy of forbearance was enacted following the crisis. However, according to a number of studies, this led to the evergreening of the loan, which in turn led to the misallocation of resources, impeding the creative destruction process. In response, various reforms, such as the IBC, were established to enhance the effective allocation of resources. So, India serves as an important case study to see whether the credit market is efficient in allocating funds to the most productive firms, i.e., flows from low to high productivity firms, and that holds important lessons for the economies where debt financing plays a major role. To our knowledge, this is the first attempt in the context of India to examine whether this economically painful period has a silver lining or not.

Against this background and motivation, we assess the validity of the cleansing hypothesis in India. This paper will specifically address the following questions: Does the process of creative destruction intensify during economic downturns? Does the pattern of reallocation change due to a change in the nature of the downturns or crises? Is credit reallocation efficiency-enhancing? If so, does the nature of the relationship between productivity and reallocation change during economic downturns? Is the relationship between productivity and reallocation we see in normal recessions different in the crisis? How does the relationship between reallocation and productivity vary during economic downturns or crises across sectors (manufacturing vs. services)? Is there any evidence that credit constraints have a negative impact on productivity?

To do this, we construct measures of credit reallocation for all publicly traded firms as well as at the sectoral level covering the period 1988–2020 and investigate the extent of credit reallocation, especially during periods of economic contraction. In the second section of the analysis, we investigate the relationship between credit reallocation and productivity using the regression specification employed by (Foster et al., 2016).

Our results reveal several intriguing insights. In the first section of our analysis, we find that the magnitude of the credit reallocation[4] is higher in an economic downturn than in an expansion, which is attributed to the higher destruction and lower credit creation. Second, we find a similar pattern in manufacturing, but no statistically significant difference in the pace of reallocation during the expansionary and contractionary phases of the business cycle in services. Third, the magnitude of reallocation varies across crises. During the Asian financial crisis, the amount of reallocation decreased due to a fall in destruction, but it surged during the Indian financial crisis due to an increase in credit destruction. During the global financial crisis, however, reallocation accelerated as a result of the government's adoption of expansionary fiscal and monetary policy.

In the second section of our analysis, we find that credit reallocation is generally efficiency-enhancing, i.e., credit flows from low-productive firms to high-productive firms, and *normal* economic downturns reinforce this efficiency-enhancing reallocation, contrary to what (Sakai & Uesug, 2020) observed for Japan. Second, we find that credit flows from low to high productivity firms in both the manufacturing and services sectors and that reallocation is cleansing during an economic downturn in manufacturing, but we did not find evidence of a cleansing effect in services. Third, we find that the cleansing effect of reallocation differs across crises. For instance, for the overall sample, we find that reallocation was efficiency-enhancing during the global financial crisis, mildly, while reallocation was efficiency-reducing during the Indian financial crisis. During the Asian financial crisis, we found no evidence of

[4] The excess credit reallocation is a more suitable index of simultaneous credit creation and destruction than gross credit reallocation Davis & Haltiwanger (1999). Therefore, to explain our result we have used excess credit reallocation as a measure of credit reallocation in India.

cleansing. Next, we find evidence of cleansing during the crisis in manufacturing but not in service. Finally, we determine that one of the potential causes for the absence of a cleansing effect could be the financial constraints on productive firms.

The subsequent sections of this paper are organized as follows. Section 2 briefly reviews the literature on economic downturns and reallocation and introduces the background of the two economic crises in India. Section 3 explains our data and construction of key variables, while Section 4 details the empirical methodology implemented. Section 5 demonstrates the results. The final section, Section 6, summarizes and concludes the research.

2. Related literature and context

2.1 Related literature

This section briefly reviews the extant literature[5] on the interrelationship between creative destruction and the business cycle. We further divide this section into two subsections. In the first subsection, we review the literature on how the extent of resource reallocation fluctuates over the business cycle. In the second subsection, we review the literature on the existence of efficiency-enhancing reallocation and how the degree of efficiency-enhancing reallocation varies over the business cycle due to changes in the nature of downturns.

2.1.1 Magnitude of the reallocation during downturns

The idea that the magnitude of resource reallocation increases during economic downturns at least dates back to the Schumpeterian view that recessions induce the process of creative destruction (Schumpeter, 1939, 1942). Schumpeter argued that less efficient firms are more likely to exit the market during economic downturns, and their resources can then be redirected

[5] It should be noted that many theoretical studies on reallocation focus on creating and destroying production arrangements rather than reallocating labour, capital, and credit. We analyse theoretical works on credit reallocation and other resource reallocation. As a result, the review of the literature contains theoretical studies not only on credit reallocation but also on the reallocation of different other types of resources. Following (Sakai & Uesug, 2020) we assume that credit and other inputs respond qualitatively the same to changes in output.

to more efficient firms. In this way, recessions promote creative destruction by "cleansing" out the unproductive firms and reallocating the resources to the relatively productive firms. Recently, this idea has been revived and investigated by a series of theoretical studies inspired by (Davis & Haltiwanger, 1990) work and who documented that economic downturns are associated with increased reallocation in the manufacturing sector of the U.S. economy.

One of the first theoretical studies by (Caballero & Hammour, 1991a) examines the industries' response to the change in aggregate demand in the vintage model of creative destruction. They emphasise that during a recession, an industry can accommodate the decrease in aggregate demand in two ways: a decline in the rate at which production units are created or an increase in the rate at which production units are destroyed. The insulation effect can occur if most of the decline in demand is accommodated by a reduction in the creation of the production unit and it partially destroys the existing production unit. Nonetheless, the insulation effect is incomplete as the destruction of production units happens, and empirical evidence (Blanchard et al., 1990; Davis & Haltiwanger, 1990) also suggests that destruction is more cyclically responsive than creation. Therefore, the (Caballero & Hammour, 1991a) model assumed the increasing adjustment cost for creating a new production unit and suggested that the number of production units destroyed during recessions exceeds the number of production units created. Depending on these theoretical results, they predict that the magnitude of reallocation will be higher during economic downturns driven by a higher level of destruction.

(Mortensen & Pissarides, 1994) also come up with a similar conclusion as (Caballero & Hammour, 1991a) that the volume of reallocation increases during recessions and most reallocation is directed by job destruction during economic downturns. A different but similar version of this hypothesis was advanced by (Aghion & Saint-Paul, 1998; Gomes et al., 2001; Hall, 1991, 2000) that recession induces productivity by driving inefficient firms from the market during downturns. (den Haan et al., 2003 propose the dynamic equilibrium model by applying the search and matching framework in the credit market that focuses on the relationship between lenders and borrowers. The formation and dispersal of the lender-borrower relationship correspond to the creation and destruction of credit. A negative shock lowers entrepreneurs' profitability destroys borrowers-lenders relationships, and decreases the credit amount outstanding and investment, leading to a "collapse" equilibrium. In their model, the extent to which these relationships break up is greater during downturns, resulting in more credit reallocation during economic downturns. The empirical evidence for the increased reallocation driven by increased destruction during a recession is provided by (Craig & Haubrich, 1999; Dell'ariccia & Garibaldi, 2005; Ana Maria Herrera et al., 2011; Junghwan Hyun & Minetti, 2019; Ramey & Shapiro, 1998).

Contrary to the studies mentioned above, which show that reallocation increases during economic downturns, another stream of literature suggests that economic downturns might lead to a decline in reallocation. (Caballero & Hammour, 2005) challenge the prevailing notion that reallocation of resources increases during economic downturns by empirically examining the cumulative response of U.S. manufacturing job flows following a negative shock. They find that economic downturns result in a reduction in cumulative reallocation. They also developed a theoretical model of creative destruction that is in line with empirical results. (Caballero et al., 2008) developed a model and predict that during downturns, there is no change in the extent of destruction due to financial assistance given to the non-profitable firms (zombies), and because of that, they do not exit the market. But the extent of creation declines in downturns due to a fall in demand. (Chamley & Rochan, 2011) introduce the credit market's search and matching framework model and report that during downturns, verification costs for projects financed by long-term loans rise and the profitability of new loans rises, banks choose to roll over loans. This bank behaviour leads to lower credit creation and destruction, resulting in a smaller extent of credit reallocation during downturns. (Sakai & Uesug, 2020) also present empirical evidence that the extent of credit reallocation declines during a recession.

2.1.2 Existence and intensity of the cleansing effect

The magnitude of the reallocation only tells us about the churning occurring in the economy but does not provide information on whether resources flow from less productive firms to more productive firms, i.e., whether reallocation is efficiency-enhancing or not. In a recession, it may happen when inefficient firms shut down and resources freed by them move to other inefficient firms instead of efficient firms due to frictions in the market. So, the next important aim of the present study is to examine the existence and extent of the cleansing effect of recessions. Here, we briefly review the extant literature on the cleansing effect of recession.

Some studies mentioned in the above section, i.e., (Caballero & Hammour, 1994; Mortensen & Pissarides, 1994), assume that resource reallocation is efficiency-enhancing. Only the most efficient production units participate in the production process in their setups. If the number of production units is insufficient based on a strict productivity ranking, other production units enter the market. Similarly, inefficient units go out of business if the number is excessive. The intensity of the cleansing effect may change during economic downturns, and some argue that the cleansing effect is more pronounced during economic downturns than in normal times, i.e., during the recession, more resources are reallocated from less efficient to more efficient firms. The theoretical macro-model (Caballero & Hammour, 1994; Gomes et al., 2001; Hall, 2000; Mortensen & Pissarides, 1994) predicts that recessions speed up the cleansing effect by driving inefficient firms out of the market and redirecting resources to efficient firms. (Becsi et al., 2005) propose the search and matching model for the access of credit to firms and find that following a negative shock, which leads to a downturn in the economy, has an unduly adverse effect on unproductive firms, leading to more lenders and borrowers' breakup during a downturn. In a recession, the gap between unproductive and productive firms in credit availability grows wider. It will increase the economy's productivity because resources will be reallocated to relatively efficient firms during downturns. Several empirical studies (Davis & Haltiwanger, 1990; Dell’ariccia & Garibaldi, 2005; Junghawan Hyun & Uddin, 2016; Junghwan Hyun, 2015; Konings, 1995; Ramey & Shapiro, 1998) also report that economic downturns are indeed associated with countercyclical reallocation.

On the other hand, some studies find no apparent evidence of the cleansing effect during economic downturns. (Bresnahan & Raff, 1991; Bertin et al., 1996) investigate the industrial behavior during the great depression of the U.S. motor industry and blast furnace industry and find that there is no correlation between reallocation and economic downturns. (Bresnahan & Raff, 1998) argue that plants were closed down during the Great Depression not because they were inefficient but because their operating costs were avoidable. (Schuh & Triest, 1998) study the deep recession in the U.S. in the early 1980s and find that job creation and job destruction were not significantly higher in the downturn. (Foster et al., 2001) also show in their analysis that there is no difference in resource reallocation during the recession and non-recession periods. (Baily et al., 2001) examine the cyclical dynamics between reallocation and productivity from 1972 to 1989 with manufacturing business data and report that reallocation shows countercyclical behavior only modestly.

Some studies criticizing the cleansing effect argue that resource reallocation during downturns is less efficiency-enhancing or even efficiency-reducing. The first strand of reasoning for this prediction focuses on the presence of market imperfections, and the second focuses on the lenders' incentive to provide financial assistance to the zombie firms during economic downturns. For example, (Caballero & Hammour, 1996) point out that reallocation may not accelerate during economic downturns due to incomplete contracts in the labor market. (Barlevy, 2002) introduces the sullying effect and finds that economic downturns drive out inefficient firms, but it may also complicate the creation of efficient firms. The calibration results of the model indicate the magnitude of the sullying effect is larger than the cleansing effect, which implies that market imperfections in a recession would outweigh the benefits of the destruction of inefficient firms. In their model (Barlevy, 2003; Osotimehin & Pappadà, 2017), they examine the reallocation of resources during economic downturns in the presence of credit market frictions. They argue that if efficient firms are more vulnerable to credit constraints, it may reverse the cleansing effect of a recession. In their study (Caballero & Hammour, 2005), they find that, cumulatively, an economic downturn leads to reduced restructuring rather than increased. According to (Ouyang, 2005), the cleansing effect is likely to be offset by the scarring effect because recessions prevent potentially young productive firms from growing and entering the market, reducing efficiency-enhancing reallocation. (Bruche & Llobet, 2014) introduce the model and report that lenders' limited liability leads to distortion in the credit market due to which, during recessions, lenders provide financial assistance to nonviable zombie borrowers. Many firm-level studies explored the effects of severe economic downturns on the reallocation of resources and provided empirical evidence that economic downturns hamper efficiency-enhancing reallocation (Bartelsman et al., 2018; Caballero et al., 2008; Domini & Moschella, 2018; Foster et al., 2016; Furceri et al., 2021; Garcia-Louzao & Tarasonis, 2021; Hallward-Driemeier & Rijkers, 2013; Kwon et al., 2015; H. J. Lee et al., 2017; Sakai & Uesug, 2020).

The theoretical models yield conflicting views on how the magnitude and intensity of the cleansing effect vary over the business cycle. The empirical evidence investigating this is also limited and ambiguous. Most of the studies mentioned above examining the cleansing effect of recessions are in the context of the labor market and mainly include developed countries like the U.S., U.K., Europe, etc. Our work contributes to the extant literature examining the cleansing effect of economic downturns in the context of developing economies' credit markets, particularly India, for which the evidence is still missing. It would be interesting to see which of the contradictory views is consistent with data for the Indian economy. Moreover, the extent to which reallocation dynamics in developing economies mimic those of developed economies is an actively researched issue (Hallward-Driemeier & Rijkers, 2013) and (Bartelsman et al., 2004) find the reallocation dynamics in developing economies are similar, so our findings can be used in the context of other developing countries.

2.2 The Indian context

This section briefly overviews the several macroeconomic event that could have affected the credit market dynamics in the India over the last three decades. It primarily focuses on the four financial crises that Indian economy experienced during the sample under analysis: the balance sheet payment crisis in early 1990s, the Asian financial crisis at end of 1990s, the global financial crisis in the late 2000s, and Indian financial crisis in the late 2010s.

Figure 1 displays three charts that convey the idea of the entity of crisis in the economy. The first economic downturn occurred in the early 1990s, which was triggered by the severe balance of payment crisis that led to the near collapse of the Indian economy. As we see from Figure 1A, during the crisis of 1991, the real per capita GDP growth rate turned negative (-0.98%), which was growing at an annual average of 4%. Figures 1B and 1C show that the manufacturing industry, which was growing at an annual average rate of 6%, declined to -2%, while the service sector was still growing at a robust growth rate of around 5%.

After the brief period of industrialization and economic growth (1993-96), the economic slowdown in 1997 rang in the end of the economic party. The prime causes of the economic contraction during 1997 were political instability and the Asian financial crisis, which originated in Thailand, posing a serious threat to the Asian region. Figure 1 shows that per capita GDP growth fell to around 2%, while value-added growth in the manufacturing industry fell to around 1% from 15% the previous year. Only the service sector bloomed at 9%. Even though growth in the manufacturing sector was slow, the GDP growth rate quickly picked up after the V-shaped recovery because the service sector was doing well.

Over the observed sample, the next economic contraction happened in 2008 due to the collapse of the U.S. financial system in the late 2000s. It is generally believed that the impact of the global financial crisis was relatively more severe than the Asian financial crisis on the Indian economy because of the rising integration of its financial market and economy with the rest of the world. It is evident (Figure 1) that the contraction of the per capita GDP was higher during the global financial crisis than during the Asian financial crisis. During the global financial crisis, per capita GDP growth contracted to 1.5% (Figure 1A) and value-added in the manufacturing sector slowed down to 6% in 2007 and further declined to 4% in 2008 (Figure 1B). The value-added growth in services declined mildly (Figure 1C) from 7% in 2007 to 6.5% in 2008 and bounced back to reach the pre-crisis level. The effects of the Great Recession didn't last long, and the Indian economy quickly bounced back with a V-shaped recovery in response to large amounts of fiscal and monetary stimulus.

Though the direct consequences of the global financial crisis on Indian banks and the financial sector were mostly limited to some stress in the Indian financial markets and the real economy (Mohan & Ray, 2019), this helped pave the way for the next big financial catastrophe in the Indian economy, namely the Indian financial crisis. To combat the global financial crisis, a policy of forbearance was adopted, allowing banks to restructure loans without having to designate them as nonperforming assets (NPAs). This policy assisted businesses in overcoming temporary challenges during the crisis, thereby averting widespread contagion. But the forbearance policy stayed in place for a long time after the crisis ended, hurting businesses, banks, and the economy as a whole. By the late 2000s, substantial corporate loans expanded, including for lumpy infrastructure projects under public-private partnerships (PPPs), and because of that, after 2014, the stress on banking and private corporate balance sheets became apparent. The RBI introduced the asset quality review, which compelled banks to recognise stressed assets. From March 2015 to March 2018, gross NPAs quadrupled to 11.5% of total bank advances. Other causes, like governance concerns in PSBs and declining commodity prices, have also contributed to the crisis's intensification.

After Lehman failed, there was an unprecedented outflow of money, and the twin-balance sheet crisis aggravated the credit crunch. While bank credit to industries fell after FY2015, bank financing to NBFCs increased. In November 2016, the government demonetized 86 percent of the economy's cash, which boosted this secular growth tendency. Businesses and households hurried to deposit their cash, resulting in an increase in bank deposits for FY2017. India experienced a Lehman moment in September 2018 when IL & FS, a major infrastructure-financing NBFC, defaulted on its debt. This caused shock waves throughout the industry, a severe credit crunch, and an impact on the real economy as well. Therefore, the 2018 NBFC crisis exacerbated the credit crunch in an economy that was already facing a downturn in bank credit. The severity of the Indian financial crisis is depicted in Figure 1. The real GDP growth rate, as well as the value-added growth in the manufacturing and services sectors, fell.

As we see, during the sample period, the Indian economy has gone through several crises, and all differ in their root causes and their repercussions in many respects. Therefore, this offers India an intriguing case study for evaluating the Schumpeter cleansing hypothesis, i.e., if a silver lining exists during economically difficult times.

3. Data and variable construction

3.1 Data and source

The primary data source for our analysis is Prowess, a database compiled and monitored by the Centre for Monitoring the Indian Economy (CMIE) for Indian businesses from 1988 to 2020.

This database is helpful for various reasons in investigating the cleansing effect of economic downturns. *First*, it is the most comprehensive database for Indian business entities and covers approx. 70% of the economic activity of the organized industrial sector (Munjal et al., 2019). *Second*, it is well-suited for analysing the effect of the economic crisis on the firms' behavior as it provides sufficient information on the pre-and post-crisis periods. *Third,* it provides detailed firm-level information retrieved from balance sheets, income, and profit and loss statements, including information on ownership, equity, sector of activity, firms' foundation and liquidation dates, assets, liabilities, value-added, revenues, and profits, allowing us to measure TFP and reallocation. *Lastly,* the Prowess database also provides information on firms operating in various industries; industry categories follow the 2008 National Industries Classification (NIC), which allows us to perform a detailed heterogeneity analysis to study the impact of the crisis across industries.

The database has been largely used for firm-level analysis in the Indian context (Bhaumik et al., 2018; Gopalan et al., 2007). It contains information on both listed (reasonably active on the stock exchange) and unlisted firms, but the information on unlisted firms is limited and not readily available. So, the universe of our firms includes only the listed firms and, being interested in firms that demand rather than supply, we exclude all firms in finance and insurance. We use annual firm-level data of listed non-financial[6] firms comprised of manufacturing and service industries. After data cleaning, we are left with a total of 1773 listed non-financial firms, of which 1359 are from the manufacturing industry and 412 are from the services industry. The data on firms' total debt and loans are retrieved from the prowess for measuring reallocation. For computing TFP, variables such as gross sales, gross fixed assets, salary and wages, number of employees, raw materials and power and fuel expenditures are used. All the variables are obtained from the Prowess and output, salaries and wages, raw

[6] Due to the lack of representation of the agriculture industry firms in our database, we have excluded them from the analysis.

materials, and energy-related deflator data are obtained from the Office of the Economic Adviser, the Ministry of Commerce and Industry, Government of India. The capital deflator is obtained from the World Development Indicators (WDI).

3.2 Construction of reallocation measures

3.2.1 Measurement issue

Following (Ana Maria Herrera et al., 2011; Junghwan Hyun & Minetti, 2019), we also define total credit (debt from firms perspectives) as all forms of financial debt except accounts payable[7] to suppliers. Besides total credit, we also study loan reallocation to all listed, manufacturing and services firms. The reallocation of bank loans across industries can have different dynamics.

Our approach to measuring gross flows faces some methodological issues. *First*, it may underestimate the gross flows because one would like to measure the reallocation of gross flows across the project, but there is no data for identifying the simultaneous contraction and expansion of gross flows within firms. The *second* measurement issue regards the entry of firms. In the prowess database, firms can enter for different reasons; some are newly founded, while others are existing firms that file with the Ministry of Corporate Affairs (MCA) and become incorporated or result from the divestiture of a larger firm. We do not wish to count the debt of an existing firm as an addition to aggregate credit. Following (Ana Maria Herrera et al., 2011; Junghwan Hyun & Minetti, 2019; Ramey & Shapiro, 1998), we drop the firms that enter for the first time in the dataset if the ratio of gross capital is greater than 20% of the net capital during a firm's first year in the dataset. The *third* is with regard to firm exit. For the

[7] There are strong reasons to exclude trade credit because it has very different properties from other kinds of debt. Trade credit is often used for transactional motives rather than for financial motives. Second, it is based on a relationship with suppliers rather than with financial institutions (Junghwan Hyun & Minetti, 2019; Nilsen, 2018). Finally, Trade credit is very expensive and firms turn to trade credit when they lack access to cheaper financing source (PETERSEN & RAJAN, 1994). Because it is expensive, firms do not depend on trade credit to finance long-term projects that have the persistent impact on firm performance. All these characteristics infer that trade credit differ along important dimensions and has low substitutability with other forms of finance (Ana Maria Herrera et al., 2011; Nilsen, 2018; RAJAN & ZINGALES, 1995).

dataset following (Ana Maria Herrera et al., 2011; Junghwan Hyun & Minetti, 2019; Ramey & Shapiro, 1998), we consider firms that exit due to merger & acquisition, liquidation, or bankruptcy as exiting firm[8], not for other reasons. The *fourth* issue is with regard to the mismatch between the fiscal year and calendar year. We handle this mismatch the same way that CompStat does: if the fiscal year ends before May 31, the data are assigned to the previous year. If the fiscal year ends after May 31, the firms' data are not changed, as if there was no mismatch. If we recalculated gross flows by splitting the fiscal year data into equal parts for each calendar year, the results were almost the same, so the original data were used. The *final* measurement issue concerns inflation. So, we deflate the original data using the implicit GDP deflator so we can look at the reallocation in real terms and compare it to real aggregate variables.

3.2.2 Aggregation

We measure the magnitude of credit reallocation and apply the well-established methodology introduced by (Davis & Haltiwanger, 1992) and utilized by (Herrera et al., 2011) to measure the extent of credit reallocation in the US. Let c_{ft} denote the average debt of firm f between $t-1$ and time t & c_{st} denote the average debt of the set of s firms between time $t-1$ and t. The growth rate of debt for a firm f at time t is denoted by g_{ft}[9]. It is defined as the ratio of change in a debt of firm f at time $t-1$ and t to the average debt of firm f between time $t-1$ and time t. More specifically,

[8] There is a strong reason to treat the exit of a merged or acquired firm as a credit subtraction. When two firms merge, the management and workforce of one obtain control over the financial resources of the other. Therefore, for the financiers of either firm, this is at least partly equivalent to reallocating credit between two firms. Indeed, a huge literature finds that the announcement of mergers significantly affects the stock market valuations of both the target and the acquirer, suggesting that mergers have important real effects (Servaes, 1991).

[9] As (Ana Maria Herrera et al., 2011) explained that g_{ft} is the monotonic transformation of the conventional growth rate measure & is roughly equal for the small growth rates. It involves two important benefits relative to the percentage change. First, it is bounded. Second, it is symmetric about zero.

$$g_{ft} = \begin{cases} 2(c_t - c_{t-1})/(c_t + c_{t-1}) & if\ c_{t-1}, c_t > 0 \\ -2 & if\ c_{t-1} > 0, c_t = 0 \\ 2 & if\ c_{t-1} = 0, c_t > 0 \end{cases} \qquad 1$$

where, the first equation denotes the continuing firm's debt growth rate, which is between the range $(-2{,}2)$. The successive equation indicates the debt growth rate for dying firms when $g_{ft} = -2$ & new-born firms when $g_{ft} = 2$.

Alike (Ana Maria Herrera et al., 2011), we also construct five credit flows measures using firms' debt growth rate. Given a set s of firms, the credit creation (POS_{st}) for set s of firms at time t is calculated by the sum of the debt growth rate of the firms with growing debt or new-born firms within the set divided by the c_{st}, the total debt growth rate of the set s of firms. It is given by:

$$POS_{st} = \sum_{\substack{f \in s_t, \\ g_{ft>0}}} \left(\frac{c_{ft}}{c_{st}}\right) g_{ft} = \frac{\sum_{f \in s_t, g_{ft} > 0}(c_t - c_{t-1})}{c_{st}} \qquad 2$$

Analogously, the credit destruction (NEG_{st}) is the sum of absolute values of the debt growth rate of shrinking or dying firms within the set divided by the total debt growth rate of the set s of firms. The equation is given by:

$$NEG_{st} = \sum_{\substack{f \in s_t, \\ g_{ft<0}}} \left(\frac{c_{ft}}{c_{st}}\right) |g_{ft}| = \frac{\sum_{f \in s_t, g_{ft} < 0}(c_{t-1} - c_t)}{c_{st}} \qquad 3$$

The sum of credit creation and credit destruction defines the gross credit reallocation (SUM_{st}) in set s between time $t-1$ and t, and the difference yields the net credit growth rate (NET_{st}). They are given by:

$$SUM_{st} = POS_{st} + NEG_{st} \qquad 4$$

$$NET_{st} = POS_{st} - NEG_{st} \qquad 5$$

In the above equation, SUM_{st}, reflects the change in debt in gross terms and NET_{st} reflects the change in net terms. We define excess credit reallocation (EXC_{st}) as

$$EXC_{st} = SUM_{st} - |NET_{st}| \qquad 6$$

The excess credit reallocation(EXC_{st}) measures the credit reallocation in excess of the minimum required to accommodate the net credit changes.

3.3 Computation of TFP

The next important variable that we construct is firm-level productivity. One of the crucial objectives of the current study is to examine whether resources flow from less efficient firms to more efficient firms. So, the correct estimation of productivity is vital. Productivity estimation continues to be challenging because of various methodological and contextual issues (Bournakis & Mallick, 2018; Khanna & Sharma, 2021; Mohapatra, 2020). The attempt to estimate the production function by employing the OLS produces the bias estimates and, further, the bias estimate of productivity because it presumes that inputs are determined exogenously. However, in reality, firms' input choices are dependent on unobservable productivity shocks, which leads to the problem of endogeneity. Several ways to deal with the problem of simultaneity have been suggested, and we can put them into three groups: the instrumental variable (IV), fixed effect (FE), and control function approach.

In the latter group, the control function approach addresses this issue by using intermediate inputs (materials and power and fuel) to proxy for the unobservable productivity shock. These methods use the two-stage procedure to correct the endogeneity: in the first stage, employing non-parametric methods to estimate the parameters of the variable input; and in the second stage, exploiting the Markovian nature of the productivity process to estimate the parameters of the capital input. The framework begins with the estimation of the following production function:

$$y_{i,t} = \alpha + \beta w_{i,t} + \gamma k_{i,t} + \omega_{i,t} + \epsilon_{i,t} \qquad 7$$

Where $y_{i,t}$ is (log) of firms output, $w_{i,t}$ is the vector of the (log) free variable such as labor and intermediate inputs, $k_{i,t}$ is the vector of the (log) state variable such as capital, $\epsilon_{i,t}$ is a normally distributed idiosyncratic error term, $\omega_{i,t}$ is the unobserved technical efficiency parameter potentially correlated with the input choices. It follows the first order Markov process:

$$\omega_{i,t} = E(\omega_{i,t}|\omega_{i,t-1}) + u_{i,t} = g(\omega_{i,t-1}) + u_{i,t} \qquad 8$$

$u_{i,t}$ is the random error term, and it is assumed to be uncorrelated with contemporaneous values of the state variable, the lagged values of the free variable and technical efficiency.

To implement the method, the pre-condition is that $m_{i,t} = f(k_{i,t}, \omega_{i,i})$ is invertible in $\omega_{i,i}$ i.e., $\omega_{i,t} = f^{-1}(m_{i,t}, k_{i,t}) = h(m_{i,t}, k_{i,t})$ and $m_{i,t}$ is strictly monotonically increasing in $\omega_{i,t}$. The level of capital is decided at time $t-1$ and the level of the free variable is decided once the productivity shock is realized. The first stage involves the estimation of the following partial linear equation:

$$y_{i,t} = \alpha + \beta w_{i,t} + \Phi_{i,t}(k_{i,t}, \omega_{i,t}) + v_{i,t} \qquad 9$$

Where we define $\Phi_{i,t} = \gamma k_{i,t} + h(m_{i,t}, k_{i,t})$. We regress $y_{i,t}$ on $w_{i,t}$ and a non-parametric estimate of Φ[10]$_{i,t}(k_{i,t}, \omega_{i,t})$. This allows us to obtain the consistent estimates of free variables parameters $\hat{\beta}$. At the second stage, by utilizing the moment condition and estimated coefficient form first stage, we can estimate the parameters of capital by rewriting the model for $y_{i,t} - \hat{\beta} w_{i,t}$ conditional on $k_{i,t}$:

$$y_{i,t} - \hat{\beta} w_{i,t} = \alpha + \gamma k_{i,t} + g(\omega_{i,t-1}) + e_{i,t} \qquad 10$$

[10] The function $\Phi_{i,t}(k_{i,t}, \omega_{i,t})$ is estimated by means of a nth-degree polynomial series.

While the two-step procedure by (Levinsohn & Petrin, 2003)[11] which is a refinement over the (Olley & Pakes, 1996) method, has been widely used (Basant & Fikkert, 1993; Bhattacharya et al., 2021; Ghosh, 2009; Khanna & Sharma, 2021; C. Lee & Won, 2021; Rath, 2018; Rovigatti & Mollisi, 2018). Recent investigations have pointed out that after the first stage of non-parametric conditioning of labor there is no variation left in the labor input to identify its coefficient (Ackerberg et al, 2015). (Ackerberg et al, 2015) exhibit that there are identification problems if labor and intermediate inputs are chosen simultaneously. (Wooldridge, 2009) introduces the new estimation procedure that addresses the identification problem by showing how to get the (Levinsohn & Petrin, 2003) estimator within a system generalized method of moments (GMM) econometric framework, which can be estimated in a single step, and by showing the right moment conditions. Therefore, for our analysis, we employ Wooldridge approach to control for biases in the parameters of our production function and, by implication, our estimates of productivity.

4. **Empirical strategy**

In the above section, we have explained the data and variables employed in the analysis. Here, we discuss the empirical strategy employed to investigate which of the conflicting theoretical views is supported by the data in the Indian context.

4.1 Magnitude of reallocation during economic downturns

One of the objectives of the current study is to investigate how the magnitude of the reallocation varies over the business cycle and whether this pattern changes due to changes in the nature of economic downturns. For this purpose, we utilize the approach employed by (Sakai & Uesug,

[11] In the latter group, the control function, OP was the first to proposes the two-stage procedure to correct the endogeneity. In their model, investment is used as a proxy for productivity shock that is unobservable to researchers but known to firm managers. The LP method makes an improvement by addressing the issue that investment is often zero in the real data. Their choice is to use intermediate materials as a proxy.

2020) to assess the magnitude of reallocation in economic downturns. We aggregate the credit creation and credit destruction to obtain the sum of credit reallocation and the magnitude of excess credit reallocation during the expansionary and contractionary periods, and then statistically examine whether the magnitude of credit reallocation is higher during economic downturns than in the expansionary phase.

This analysis requires us to identify the period of the economic downturn, and for that, we employ two definitions of the economic downturn. Our first definition focuses on the economic downturns (*normal* recessions) that occur at the short-term business cycle frequencies. We utilize the dates of peaks and troughs of the business cycle officially reported by the Economic Cycle Research Institute (ECRI) and characterize the recession from peak to trough. As the business cycle dates are reported monthly, following (C. Lee & Won, 2021), we define a *year* as a "*normal* recession" from a peak to a trough when it has more than six months in the downturn. There were seven recessions[12] in the period under analysis (1988-2020), each of which was followed by an expansionary period.

The second definition focuses on the *severe* economic downturns (crises) to further explore whether the pattern changes due to the change in the nature of the economic downturns. The Indian economy has gone through several major crises during the sample under analysis (1988-2020) such as the balance sheet payment crisis in 1991[13], the Asian financial crisis in 1997, the great recession in 2008 and India's financial crisis (or India's Lehman moment) in 2018. All crises were different in their underlying causes and repercussions on the Indian economy. To assess the magnitude of the reallocation during the *severe* economic downturns (crises), we have identified the following: 1998–2000, 2008–10, and 2016–2019 as the crisis[14] periods.

[12] 1990-91, 1994, 1996, 2000-2002, 2004, 2010-2012, 2016-2020.
[13] Due to the limited number of observations in the early 1990s, the 1991 balance sheet payment crisis cannot be analysed in our study.
[14] The identified crisis periods are in line with the existing literature (Domini & Moschella, 2018; Foster et al., 2016; C. Lee & Won, 2021; H. J. Lee et al., 2017), and for India's financial crisis, we followed the economic surveys of India and (Subramanian & Felman, 2019).

4.2 Efficiency-enhancing reallocation

The empirical approach outlined above simply tells us about the volume of churn in the economy. It doesn't tell us if reallocation is efficiency-enhancing, i.e., whether resources flow from less productive firms to more productive firms, causing less productive firms to go out of business while more efficient firms grow. Taking this into account, we focus on the existence and intensity of efficiency-enhancing credit reallocation. To do so, we investigate the relationship between credit reallocation and firm productivity. We begin by employing a simple regression model, following (Foster et al., 2016; Sakai & Uesug, 2020), that connects the growth rate of our debt variables to firm productivity. The following equation represents the baseline specification:

$$g_{ft} = \alpha + \beta TFP_{ft-1} + \gamma Cycle_t + \theta X_{ft-1} + \xi IFE_i + \epsilon_{ft} \qquad 11$$

where g_{ft}[15] represents the debt growth rate of the firms, which is calculated as the ratio of the first difference between the firm f debt from time $t-1$ and time t divided by the firm average debt from time $t-1$ and time t. TFP is the firm's total factor productivity at time $t-1$. $Cycle_t$ signifies the state of the economy at time t, which is computed by applying the HP filter to the real gross domestic product, while the vector X_{ft-1} denotes the set of control variables, namely firms' growth as proxied by the rate of sales growth, firm size as measured by the log of firms' assets, firms' net worth as measured by the capital ratio, and firms' internal cash flow as measured by operating profits normalised by total assets. IFE_i represents the industry dummy. We assume a one-period lag of these explanatory factors as firm productivity and other firms' characteristics may be endogenously determined. Of particular interest to us is the value of coefficient β. If $\beta > 0$, then there exists efficiency-enhancing reallocation, i.e., credit flows from less efficient to more efficient firms.

[15] For the detailed explanation please refer to section 3.

To determine whether economic downturns strengthen or decrease the efficiency-improving reallocation, we apply two distinct techniques that represent the duration of the economic downturn (s) under consideration. First, we explore how the intensity of efficiency-improving reallocation changes during normal economic downturns that occur with high frequency. Specifically, we add an interaction term between total factor productivity and the state of the aggregate economy to the equation:

$$g_{ft} = \alpha + \beta TFP_{ft-1} + \gamma cycle_t + \delta\left(TFP_{ft-1} * cycle_t\right) + \theta X_{ft-1} + \xi IFE_i + \epsilon_{ft} \qquad 12$$

If δ is negative, it would mean that economic downturns strengthen the efficiency-enhancing reallocation and provide evidence in support of the cleansing effect of the recession; if it δ is positive, it would mean that the recession weakens the efficiency-enhancing reallocation.

Next, we add the crisis term to the regression equation to see if the pattern of reallocation changes as a result of a change in the nature of economic downturns (or crises).

$$g_{ft} = \alpha + \beta TFP_{ft-1} + \gamma crisis_t + \pi\left(TFP_{ft-1} * crisis_t\right) + \theta X_{ft-1} + \xi IFE_i + \epsilon_{ft} \qquad 13$$

If the Schumpeterian cleansing view is correct, we expect π to be positive, implying that a crisis period improves the efficient reallocation of resources.

5. Results

In the first part of this section, we discuss the results of the magnitude of the reallocation and how this pattern evolves over the business cycle by employing different methods discussed in Section 4. In the next part of the section, we present the results of the efficiency-enhancing reallocation during economic downturns and how this intensity varies over time in the underlying shocks of the crises for both the entire sample and the sector level.

5.1 Magnitude of reallocation during economic downturn

We start by displaying graphically the evolution of the credit flows constructed from total debt for publicly traded non-financial firms during the sample period (1989–2020). Panel A of Figure 2 shows annual credit creation (POS, dashed black line) and credit destruction (NEG, dashed grey line). Panel B plots credit reallocation (SUM, dashed black line) and excess credit reallocation (EXC, dashed grey line), and Panel C depicts the net credit change (NET, dashed grey line). The area tinted in light grey indicates the short-term economic downturn periods discussed in Section 4.

{Please insert Figure 2}

There are two noteworthy aspects of the evolution of these reallocation measures. *First*, it is evident that during downturns, credit destruction rises while credit creation declines. For instance, during an economic expansion (the early 1990s and mid-2000s), credit creation was significantly more than credit destruction. Thereby, NET, SUM, and EXC reached their peaks over the same period, indicating that creation drove the overall shift in reallocation. However, during the downturn, represented by the shaded grey region, credit creation declines, and credit destruction increases. *Second*, it is intriguing to note that the pattern of reallocation altered during the economic crisis of 1991 and India's financial crisis (2016–19), as observed during *normal* economic downturns and other *crises* over the sample period. However, credit destruction surged during India's financial crisis, and credit creation decreased even more drastically than during the AFC and GFC similar to what was observed by (Foster et al., 2016) during the great recession in the U.S. India's financial crisis appears to be more severe than the economic crisis of 1991.

{Please insert Figure 3}

Figures 3 and Figure 4 illustrate the evolution of credit reallocation for the manufacturing and services sectors, respectively. The three panels of Figure 2 and Figure 3 depict annual credit creation (POS, dashed black line), credit destruction (NEG, dashed grey line), credit reallocation (SUM, dashed black line), excess credit reallocation (EXC, dashed grey line), and net credit change (NET, dashed grey line), along with shaded recession periods. During the short-term recession, the manufacturing sector also experienced a decline in credit creation and an increase in credit destruction. However, this pattern appears to have changed during India's financial crisis, where credit destruction is on the rise but a decline in credit creation is chronic and persistent.

{Please insert Figure 4}

In contrast, the services industry appears to be less influenced by domestic economic slowdowns than the manufacturing sector. It is also crucial to highlight that foreign direct investment in India has been heavily concentrated in the services sector (Sönmez, 2018); hence, the services sector is more impacted by the development in the foreign market. Figure 4 shows that during the dot-com bubble burst in the early 2000s, the global financial crisis in 2008, and the taper-tantrum in 2013, credit creation in the service sector increased significantly compared to earlier periods. This significant increase in credit may be due to the lack of funds available in the foreign market. In the wake of the crisis, foreign direct investment (FDI) may have decreased as foreign investors reduced their investment and borrowing became more expensive in the international market.

{Please insert Table 1}

Table 1 shows the magnitude of reallocation measures for publicly traded non-financial firms (overall), manufacturing, and services sectors, calculated on the basis of total debt taken by firms. The columns show the average credit creation (POS), destruction (NEG), reallocation

(SUM), net credit change (NET), and excess reallocation (EXC). The annual average rate of credit creation for all firms is 16.8%, while credit destruction is 6%, resulting in credit reallocation and net credit growth of 22.8% and 10.7% over the sample period. The excess credit reallocation is 11.8% and it is considered a more suitable index of simultaneous credit creation and destruction than gross credit reallocation because, unlike gross credit reallocation (SUM), it does not increase with the absolute value of net credit. Therefore, it provides a more accurate picture of the credit[16] market dynamics (Davis & Haltiwanger, 1999). The simultaneous creation and destruction of credit indicates that some firms are increasing their debt while others are decreasing their debt, providing clear evidence of the Schumpeterian creative destruction required for market economic growth. If we compare the credit reallocation, which is around 23%, with the credit reallocation obtained by the (Ana Maria Herrera et al., 2011) for the U.S., which is around 18%, we find that reallocation is higher for India compared to the U.S. The volume of churning is greater in emerging or economies in transition as compared to developed economies (Bartelsman et al., 2004).

The average rate of credit creation for manufacturing firms is 16.1%, while the average rate of credit destruction is 6%. The corresponding figures for the service firms are 20.7% of credit creation and 5.5% of credit destruction. Meanwhile, the average rate of credit reallocation is 22.2% for the manufacturing firms and 26.3% for the services sector firms; the average net credit change is 10% for the manufacturing firms and 15% for service sector firms; and the average excess credit reallocation is 11.1% for the manufacturing firms and 9% for the service sector firms. These figures suggest that an analysis of net credit alone can be misleading as it hides a substantially large amount of reallocation.

[16] For instance, assume that credit creation rises by 20% but there is no change in credit destruction. Here, credit reallocation is 20%, but excess credit reallocation equals 0 because no credit is reallocated from one borrower to another. We can also say that changes in SUM and NET are equivalent. So, the excess credit reallocation provides an accurate picture of the credit market, and for this reason, for further analysis, we will use EXC, not SUM, as the credit reallocation measure.

Next, we discuss the results of how the pattern of credit reallocation changes due to changes in the state of the economy. For this, we divide the entire period into *normal* economic downturns and expansions to examine if there is a significant difference in the magnitude of credit reallocation. Table 1 shows the results of comparing *normal* economic downturns and expansions for publicly traded non-financial firms (overall), manufacturing firms, and service firms, respectively. First, all reallocation measures differ significantly between expansionary and recessionary periods for publicly traded non-financial firms. We can observe from table 1 that during an economic downturn, on average, there is a decline in credit creation from 21.4% to 12.3% and a rise in credit destruction from 4.5% to 7.5%, leading to an increase in the excess credit reallocation from 9% to 14.4%. So, we can say that an increase in the magnitude of excess credit reallocation during economic downturns is mainly due to the increase in destruction and a decline in creation. Qualitatively similar results are obtained for manufacturing firms and the difference between the expansionary and recessionary phases is larger and highly significant, while for the service sector the difference between the magnitude of reallocation measures between the expansionary and recessionary periods is smaller and for NEG and EXC it is negligible and insignificant. As we've previously discussed, it's not surprising that service firms are less affected by short-term economic downturns than manufacturing firms.

{Please insert Table 2}

We did a similar analysis using the alternative measure of debt, i.e., bank loans taken by publicly traded non-financial firms, manufacturing, and service firms, respectively. We find qualitatively similar results that during economic downturns, the magnitude of excess credit reallocation increases due to a decline in the creation and an increase in the destruction of credit.

{Please insert Table 3}

Table 3 presents the magnitude of the reallocation in different crises observed during the sample period. We compare the magnitude of the reallocation measure during the Asian financial crisis (*hereafter*, AFC), the global financial crisis (*hereafter*, GFC), and the Indian financial crisis (*hereafter*, IFC). For all listed firms, during the AFC, the magnitude of reallocation declined due to the fall in destruction and almost no change in credit, but during the GFC, there was a drastic increase in credit creation and more or less the same destruction in credit. It might be due to the fact that during the GFC, the Indian economy was highly integrated with the world economy, so to mitigate the effect of the GFC, the government took expansionary fiscal and monetary policy measures, which led to an increase in the reallocation. The effect of the GFC was short-lived, and the Indian economy quickly recovered from it. It is noteworthy that the pattern of reallocation measures observed during the AFC in India is similar to that documented by (Sakai & Uesug, 2020) for Japan, where reallocation declined during the recession due to a fall in destruction and more or less stable credit creation. The increase in the volume of excess credit reallocated during the IFC was due to the rise in destruction, but the drastic fall in credit creation is worth noting. The IFC appears to have the most effect on the Indian economy among all the crises witnessed during our sample. Comparing the extent of reallocation during the IFC in India to that revealed by (Foster et al., 2016) for the United States during the Great Recession, we may conclude that the severity of the IFC for India is comparable to that of the Great Recession for the United States.

To summarize, the amount of reallocation, as measured by EXC, is greater during *normal* economic downturns than during expansions, and this is mostly due to the larger NEG during recessionary times. This finding of a greater magnitude of credit destruction and reallocation during recessions is consistent with the Schumpeter cleansing hypothesis, which states that during economic downturns, destruction increases, resulting in a greater magnitude of reallocation during recessions than during expansions. When compared to the findings by Japan (Sakai & Uesug, 2020), as debt financing plays a major role in Japan, it indicates that during a recession, reallocation declines, which is primarily due to a decline in credit destruction and a similar level of credit creation, but our findings are consistent with (Davis & Haltiwanger, 1990; J. Hyun, 2016).

5.2 Efficiency-enhancing reallocation

Having addressed magnitude of reallocation during economic downturns, we examine whether this reallocation is efficient and, if so, how the intensity of efficiency-enhancing reallocation changes as nature of economic downturns alters.

5.2.1 Cleansing effect (overall)

Table 4 displays the results of our baseline estimation using equation 11 from section 4.2. Our primary variable of interest is the log of total factor productivity (*hereafter*, TFP). TFP has a statistically significant positive coefficient, which indicates that the debt growth rate is higher for the more productive firms than for the less productive firms: a one-unit increase in log-productivity leads to a one-percentage-point rise in the average firm debt growth rate (Model 1). This finding suggests that credit reallocation is generally efficiency-enhancing, i.e., credit flows from less productive firms to more productive firms.

{Please insert Table 4}

Next, we estimate equation 12 to examine whether normal economic downturns accelerate or attenuate the efficiency-enhancing reallocation. The negative and statistically significant estimated interaction effect between the TFP and the state of the economy implies that short-term economic downturns accelerate the productivity-enhancing reallocation (Model 2), which provides the evidence for the Schumpeterian cleansing hypothesis. Our results[17] are in line with those of (Caballero & Hammour, 1994; Dias & Robalo Marques, 2021; Foster et al., 2016) studies for the U.S. and Portugal and are contrary to results obtained by (Sakai & Uesug, 2020) for Japan. Model 3 and Model 4 estimate the examine the impact of different crises (AFC and GFC) on the productivity-enhancing reallocation. While the effect increases for the AFC, although insignificant, it also does not reduce the magnitude of the efficiency-enhancing reallocation. The positive and significant interaction term (TFP*GFC) suggests that productivity-enhancing reallocation strengthened during GFC.

Lastly, it's worth taking a quick look at the results for the other variables used as controls to explain the results. They are in line with extant literature. The positive and significant on $Sales\_growth_{t-1}$ coefficient indicates that a fast-growing company requires more funding. The coefficient of return on assets (ROA) and $lnAssets_{t-1}$ are positive and significant , indicating that large[18] and profitable firms require more external finance, which is consistent with the findings of (Abor, 2005; Banerjee & Duflo, 2014; Margaritis & Psillaki, 2010; Mazur, 2007). Finally, $Capital\_ratio_{t-1}$, which measures a firm's creditworthiness, has coefficients that are both positive and significant, showing that firms with a high capital ratio are more likely to be able to secure outside financing than those with a low capital ratio.

{Please insert Table 5}

The response of heterogeneous firms to the crisis may be influenced by factors that are not entirely captured by our variables. Mainly, unobservable attributes that are time-invariant but changed by the unanticipated shock may introduce bias into the estimation of coefficients. To

[17] Despite a relatively small value of R-squared there is interesting set of finding. It is also important to note that similar values are obtained by (Carreira & Teixeira, 2016)

[18] According to (Mazur, 2007), profit margins are more closely linked to firm size, and larger enterprises are less likely to go bankrupt due to their greater level of diversification. Due to a low bankruptcy rate, large corporations are able to take on greater debt. Larger companies are able to eliminate market information asymmetries and more easily obtain financial resources, both of which have a positive impact on a company's financial performance.

account for this, we estimate equations 11 to 13 by including firms' fixed effects[19]. Table 5 shows the result after including the firm's fixed effect and confirms the main result from Table 4 that productivity-enhancing reallocation is at work, and recession further strengthens this efficiency-enhancing reallocation. However, in this case, it is apparent that the interaction term (TFP*AFC) is still insignificant, but (TFP*GFC) is still positive but has become insignificant, which was barely significant at 10% when we employed the latter.

{Please insert Table 6}

Table 6 reports the results of the sub-sample analysis. The estimated coefficient of TFP is statistically significant and positive (Column 2-3), but the magnitude of the coefficient declined from 0.023 percentage points (1991-2007) to 0.005 percentage points (2008-2020). The economic downturns weakened the efficiency-enhancing reallocation during the sub-sample (1991–2007), but it seems to have improved during the sub-sample (2008–2020), though insignificant.

5.2.2 Cleansing effect (Sectoral analysis)

Our dataset also enables us to examine whether a crisis can have distinct impacts on different industries. This is particularly intriguing because, in India, the service sector plays a significant role as it contributes to around 60% of the GDP and also contributes significantly to India's total exports. In contrast, the Indian manufacturing sector's share of the nation's gross domestic product (GDP) has remained roughly constant at 16 percent over the past five decades, while its contribution to employment creation has fallen (Rath, 2018). By applying our empirical approach separately to the manufacturing and services sectors, we are able to contribute to the discussion over how a move towards a service economy influences economic growth and how

[19] Note that industry dummies are omitted from the equations 2 to 5 in the fixed effect regressions.

recessions affect these sectors differently. To investigate this, we estimate equations (11–13) for both the manufacturing and services sectors.

{Please insert Table 7}

Table 7 presents the results for the manufacturing sector. The coefficients of TFP are all positive and statistically significant (Model 1–Model 4). This suggests that credit reallocation in the manufacturing sector has been efficiency-enhancing, i.e., more credit flows to highly productive firms. The results also indicate the strengthening of the effect during economic downturns; the coefficient of (TFP * GDP) is negative and statistically significant (Model 2). In addition to this, (Model 3 and Model 4) show that the positive effect of efficiency-enhancing reallocation declined during the AFC, though not significant. At the same time, during the GFC, it strengthened (the coefficient of TFP*GFC is positive and significant).

{Please insert Table 8}

The results of the services sector are given in Table 8. The first noticeable result is that the estimated coefficient of the TFP is positive and significant, indicating that the reallocation is efficient in the service sector: a one-unit increase in log-productivity leads to a .007 percentage-point increase in the average firm debt growth rate (Model 1). Of primary interest, the coefficient of TFP*GFC is positive and not statistically significant; therefore, there is no cleansing effect during economic downturns in the service sector (Model 2). Also, there is no evidence of a cleansing effect in the service sector during the crisis period as coefficients of the interaction terms between AFC and GFC are not significant (Models 4 and 5).

5.2.3 Indian financial crisis

Next, we discuss the results of the relationship between reallocation and productivity during the Indian financial crisis. Results are reported in Table 9.

{Please insert Table 9}

The positive and statistically significant coefficient of TFP suggests that credit reallocation is productivity-enhancing for the overall economy. The one percentage increase in the firm's productivity will lead to a 0.013 percentage point increase in the average firm's debt growth. The interesting thing to note is the negative and statistically significant interaction term between TFP and IFC (Column 1), suggesting that reallocation was less efficiency-enhancing during IFC. The magnitude of the overall TFP declined from 0.013 percentage points to 0.003 percentage points (adding -0.010). Looking at the manufacturing sector (Column 2) indicates that reallocation was efficiency-reducing, i.e., more credit was being allocated to the relatively less productive firms. For, the service sector, the interaction term (TFP*IFC) is negative but insignificant, so we cannot conclude whether efficiency-enhancing reallocation declined during the Indian financial crisis or not.

5.2.4 Role of the financial constraints

The results of Table 9 suggest that the reallocation was less efficiency-enhancing for the publicly traded non-financial firms and for the manufacturing sector it was even efficiency-reducing during the Indian financial crisis. Though, it is still not clear why reallocation was efficiency-reducing during the Indian financial crisis. One reason why the cleansing effect might not have worked could be the presence of financial constraints.

We examine the validity of this explanation by dividing firms in the dataset based on the size of their leverage ratio. Small and highly indebted businesses are more likely to face financial constraints during a recession because lenders who know little about them or are concerned about moral hazard by these firms are hesitant to lend to them. We expect enterprises with a greater debt-to-equity ratio (those in the fourth quartile) to be more financially constrained than those with a lower debt-to-equity ratio due to differences in the severity of problems created by information asymmetry (firms that belong to the first quartile).

{Please insert Table 10}

Table 10 shows results for firms with a low and high leverage ratio. The magnitude of the coefficient TFP for firms with a low leverage ratio is higher than for firms with a high leverage ratio. This indicates that credit reallocation is less efficient for firms that are financially constrained, while it is more efficiency-enhancing for firms that are less likely to be financially constrained. During economic downturns, the effect is intensified for low-leveraged firms. Our results are in line with those reported by (Sakai & Uesug, 2020) for Japan.

6. Conclusion

Despite the importance of financial inputs (such as external finance) in the firms' performance, the majority of studies focus on the reallocation of job and capital. The present study fills a lacuna in the literature by providing novel evidence on the cleansing effects of recessions involving different sectors of the economy and in the context of developing economies' credit markets, particularly India's. To do so, we examine whether credit reallocation intensifies during an economic downturn using comprehensive firm-level data for publicly traded firms from 1988 to 2020, and then we look at the relationship between credit reallocation and productivity.

Our results reveal several intriguing insights. *First,* we find that the magnitude of the credit reallocation is higher in an economic downturn than in an expansion, which is attributed to the higher destruction and lower credit creation. *Second*, we find a similar pattern in manufacturing, but no statistically significant difference in the pace of reallocation during the expansionary and contractionary phases of the business cycle in services. *Third,* we find that credit reallocation is generally efficiency-enhancing, i.e., credit flows from low-productive firms to high-productive firms, and *normal* economic downturns reinforce this efficiency-enhancing reallocation. *Fourth*, we find that economic downturns induce efficiency-enhancing reallocation in manufacturing but not in services. *Fifth*, we find that the cleansing effect of reallocation differs across crises. For instance, for the overall sample, we find that reallocation was efficiency-enhancing during the global financial crisis, mildly, while reallocation was efficiency-reducing during the Indian financial crisis. During the Asian financial crisis, we found no evidence of cleansing. *Next*, we find evidence of cleansing during the crisis in manufacturing but not in service. This suggests that recessions do not have a uniform cleansing effect on the economy and that accounting for disparities between industries is critical for understanding the aggregate impact of recession cleansing effects. *Finally*, we determine that one of the potential causes for the absence of a cleansing effect could be the financial constraints on productive firms.

These findings have far-reaching policy ramifications. If recessions are cleansing, counter-cyclical policies enacted to stabilise the business cycle may impede long-term economic growth. If the opposite is true, special emphasis should be paid to the short-and long-term effects of a weaker reallocation process, which may further reduce productivity growth and economic growth. In this context, the policy response to severe non-cleansing recessions should include counter-cyclical policies aimed at shortening the duration and depth of the recession, thereby restoring the full potential for productivity-enhancing reallocation.

The limitation of the present study is that we mostly answer the question of what happened during recessions and crises but did not directly explain why this pattern is distinct. Future research can investigate why this pattern varies among sectors and crises.

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Figure 1: Macroeconomic figures (1987-2020)

Figure 1A

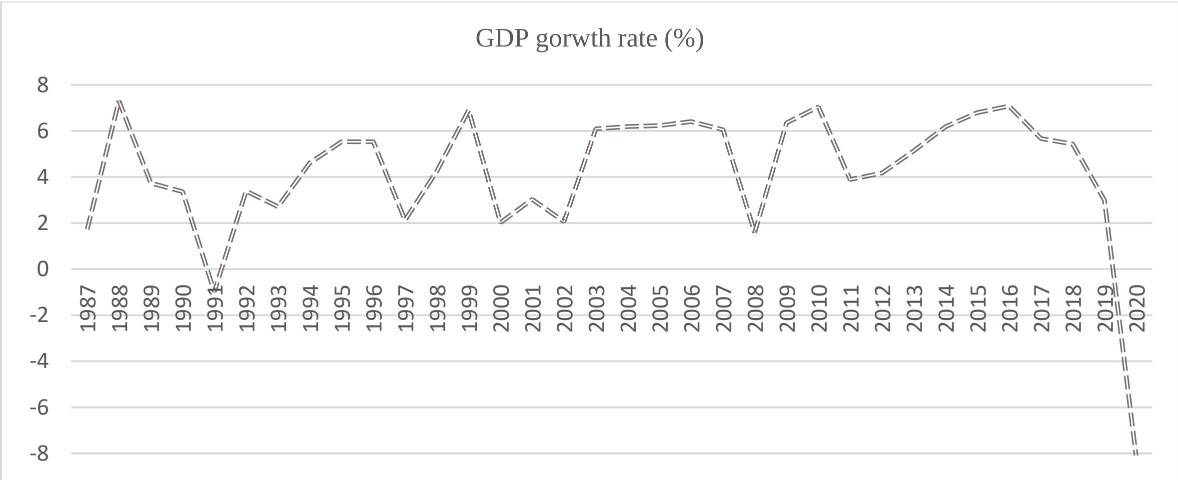


Figure 1B

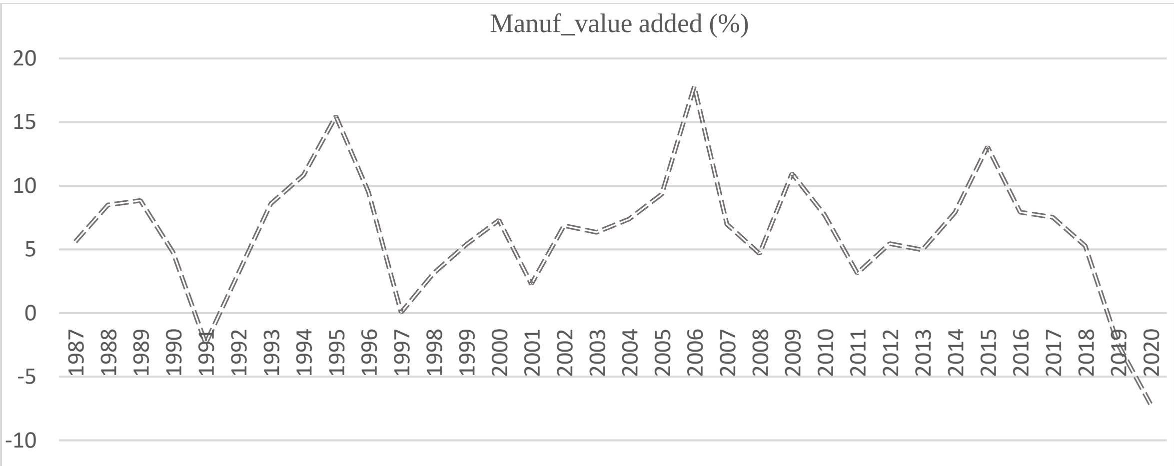
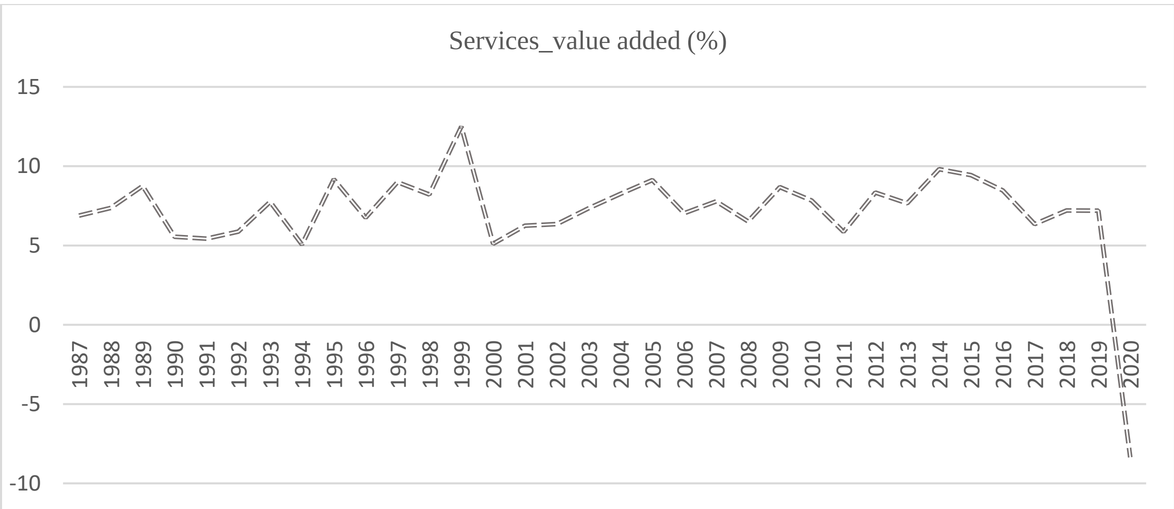


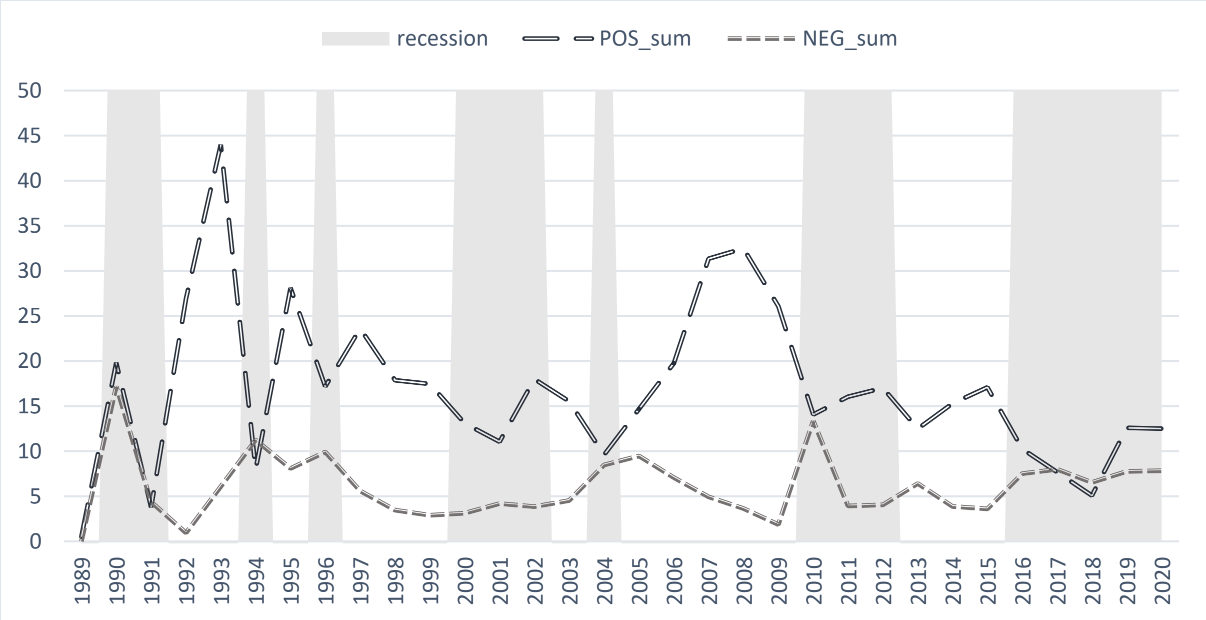
Figure 1C



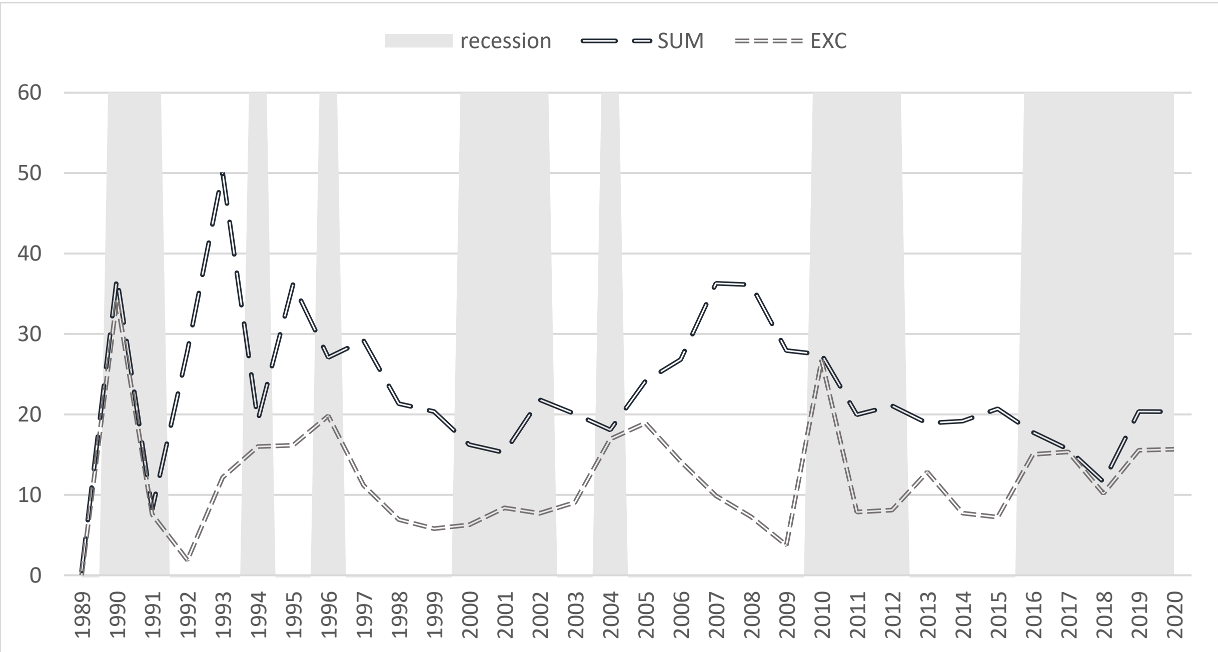
Note: Figure 1 shows the a) GDP per-capita growth rate b) manufacturing value-added growth rate c) services value-added growth rate during the sample period (1987-2020). Source: World Development Indicators (WDI)

Figure 2: Evolution of credit reallocation of publicly traded non-financial firms

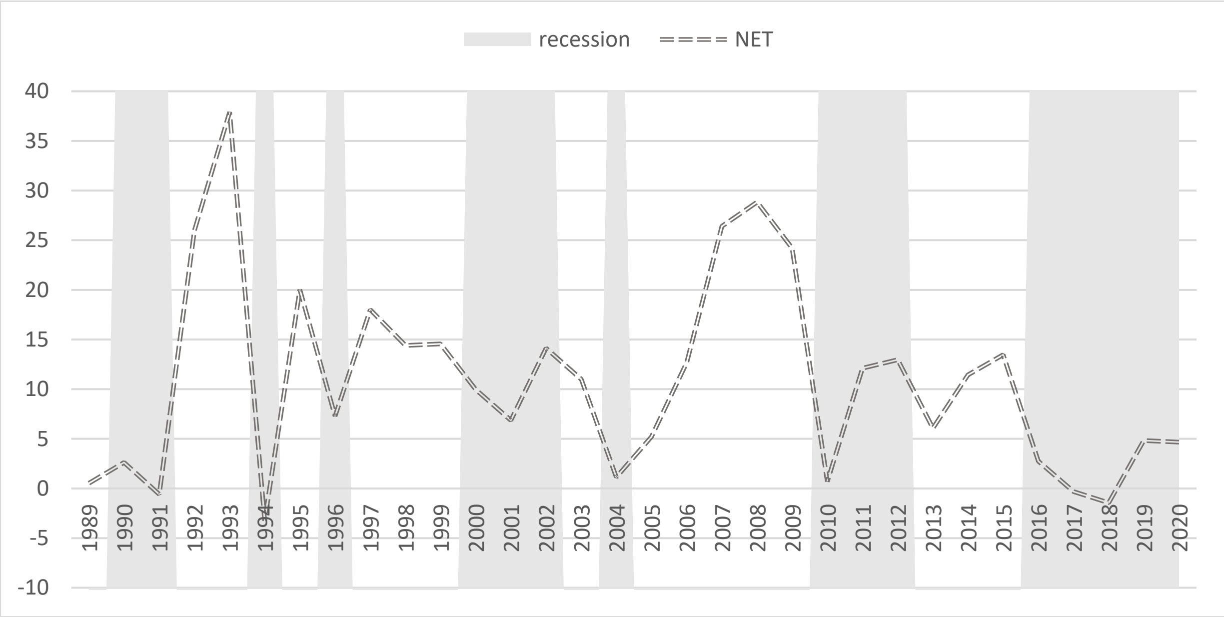
Panel A



Panel B



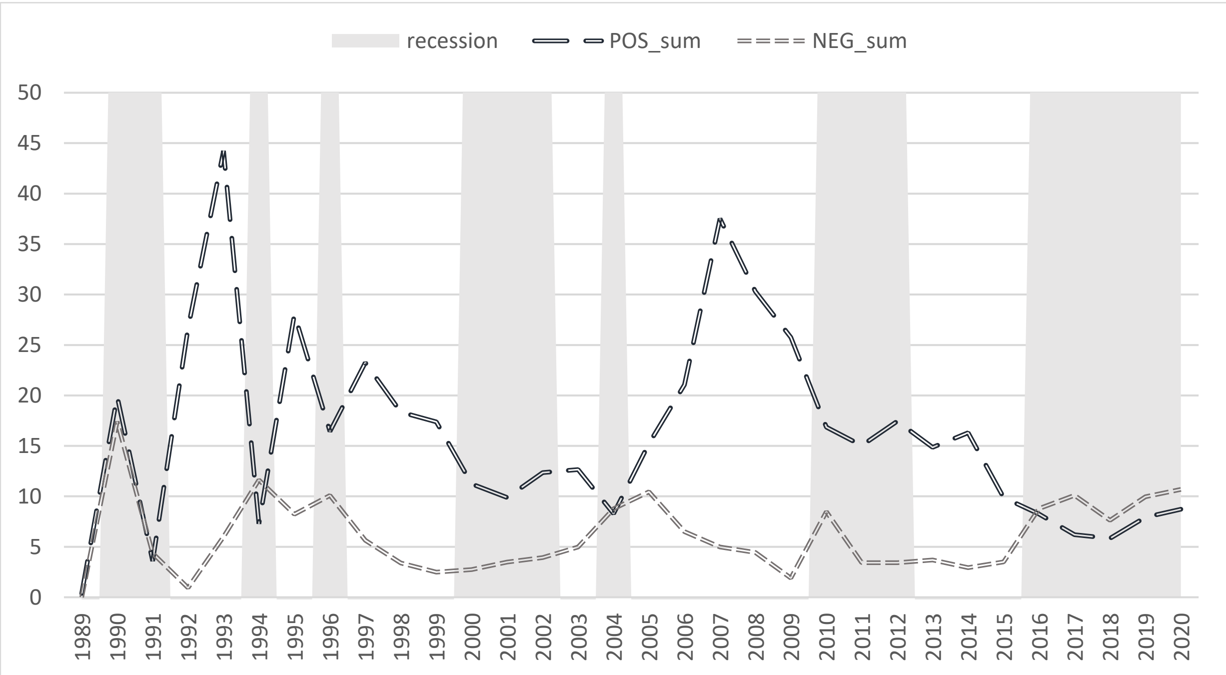
Panel C



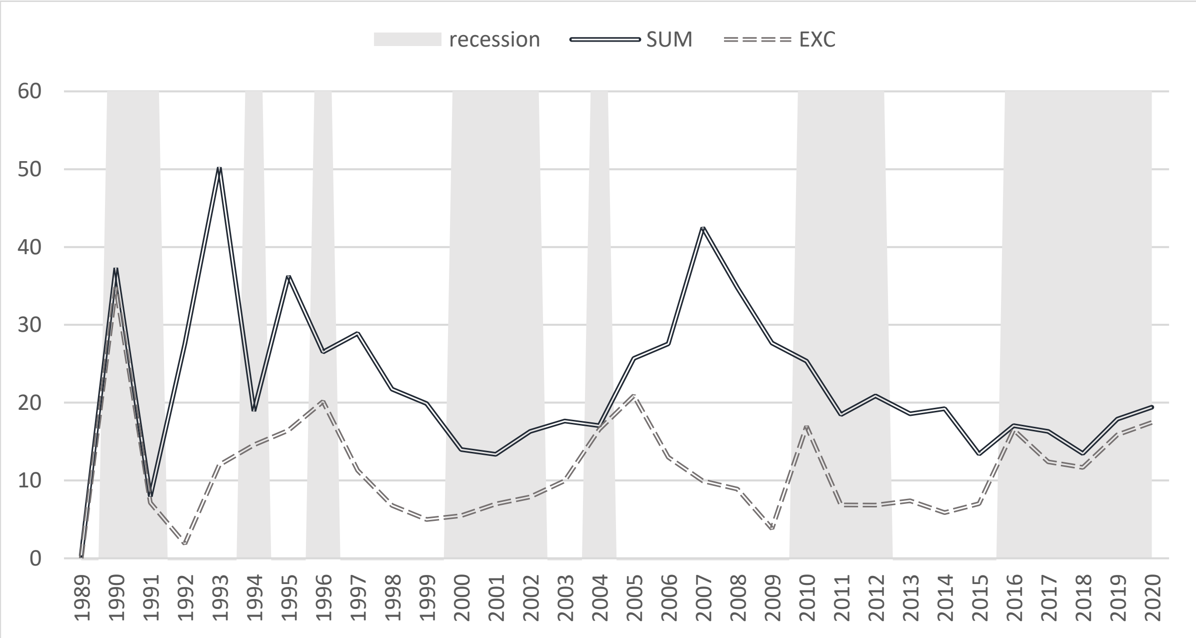
Note: This figure depicts developments in the credit reallocation measures over the entire observation (1989–2020) period. We use total debt as the credit variable. Gray shaded areas represent short-term recessionary periods. Here, POS_sum denotes the credit creation, NEG_sum denotes the credit destruction, SUM denotes the gross credit reallocation, EXC denotes the excess credit reallocation, and NET denotes the net credit growth rate.

Figure 3: Evolution of credit reallocation of the manufacturing sector firms

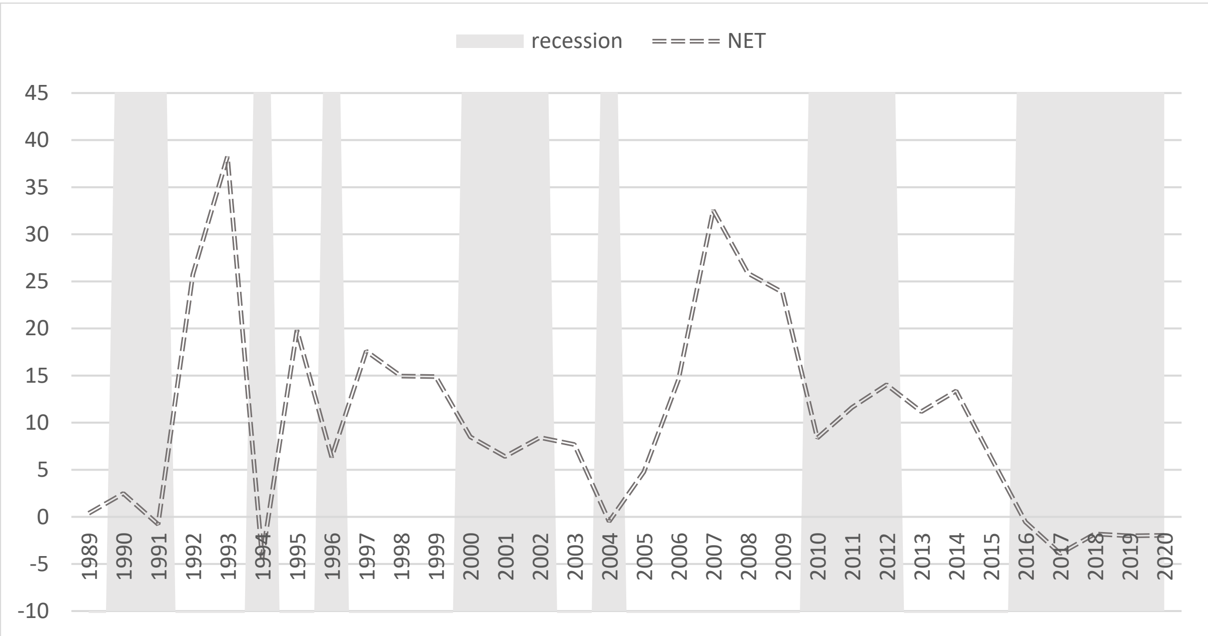
Panel A



Panel B



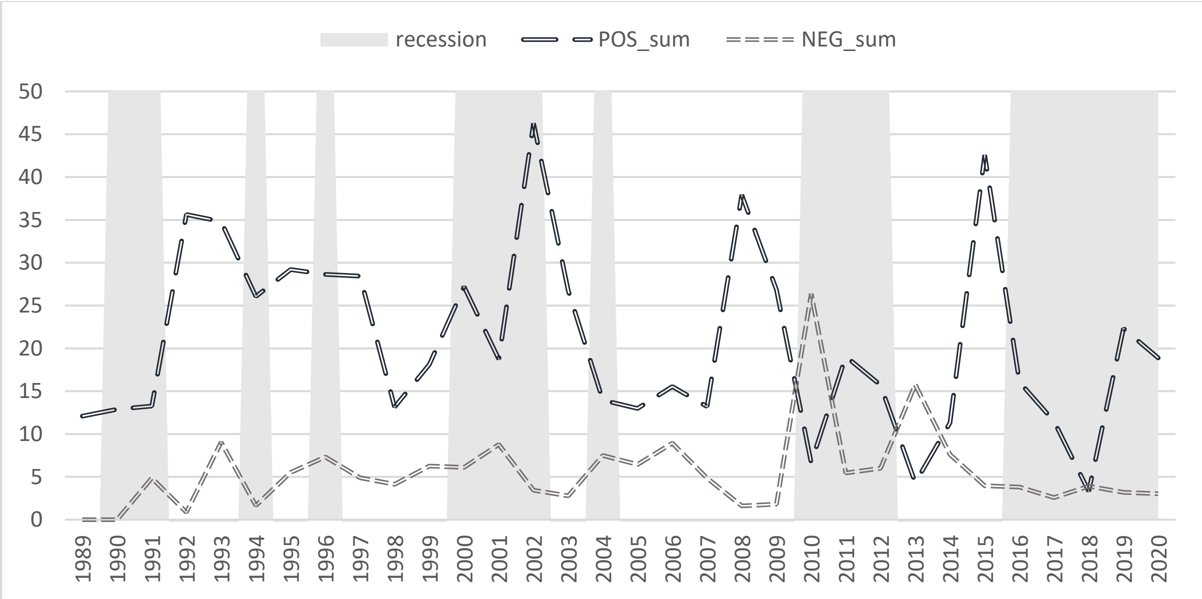
Panel C



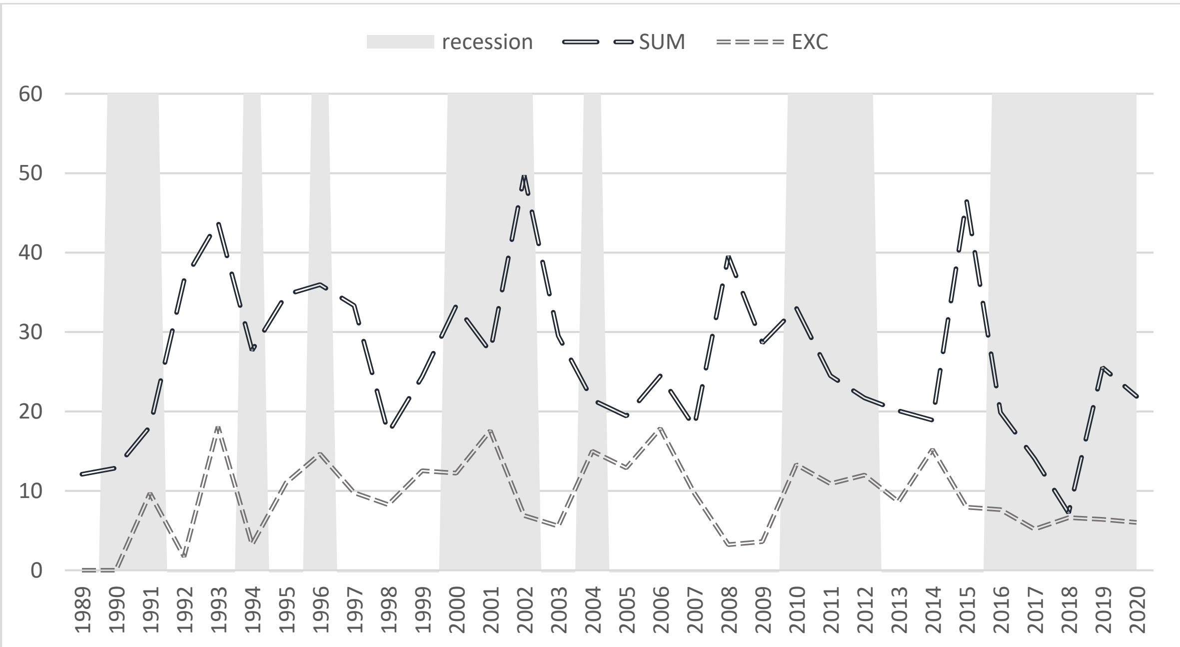
Note: This figure depicts developments in the credit reallocation measures over the entire observation (1989-2020) period. We use total debt as the credit variable. Gray shaded areas represent short-term recessionary periods.

Figure 4: Evolution of credit reallocation of the services sector firms

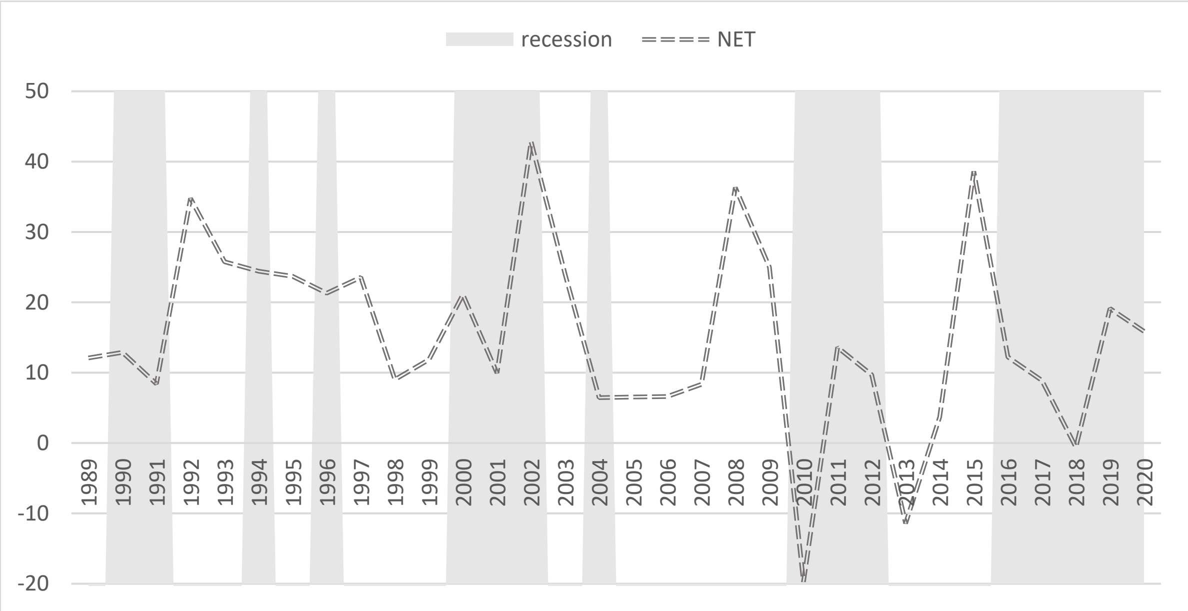
Panel A



Panel B



Panel C



Note: This figure depicts developments in the credit reallocation measures over the entire observation (1989-2020) period. We use total debt as the credit variable. Gray shaded areas represent short-term recessionary periods.

Table 1: Magnitude of credit reallocation (total debt)

All firms					
	POS	NEG	SUM	NET	EXC
Entire period	16.841	6.058	22.899	10.784	11.765
Expansion	21.449	4.530	25.978	16.919	9.059
Recession	12.234	7.586	19.820	4.648	14.470
H0: Expansion = Recession	***	***	***	***	***
Manufacturing					
	POS	NEG	SUM	NET	EXC
Entire period	16.159	6.094	22.253	10.065	11.198
Expansion	21.366	4.381	25.747	16.985	8.762
Recession	10.951	7.807	18.758	3.145	13.633
H0: Expansion = Recession	***	***	***	***	***
Services					
	POS	NEG	SUM	NET	EXC
Entire period	20.731	5.577	26.309	15.154	9.170
Expansion	22.680	5.279	27.958	17.401	9.127
Recession	18.783	5.876	24.659	12.907	9.213
H0: Expansion = Recession					

Note: This table reports the magnitude of credit reallocation of total debt for all non-financial firms, manufacturing firms and service firms. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Table 2: Magnitude of credit reallocation (bank loans)

All firms					
	POS	NEG	SUM	NET	EXC
Entire period	22.576	11.382	33.957	11.194	17.479
Expansion	30.367	8.359	38.726	22.007	16.258
Recession	14.785	14.404	29.189	0.381	18.701
H0: Expansion = Recession	***	***	***	***	
Manufacturing					
	POS	NEG	SUM	NET	EXC
Entire period	22.762	11.156	33.918	11.607	15.788
Expansion	30.988	7.722	38.711	23.266	15.444
Recession	14.536	14.589	29.125	-0.052	16.133
H0: Expansion = Recession	***	*	***		
Services					
	POS	NEG	SUM	NET	EXC
Entire period	22.351	13.933	36.284	8.418	16.953
Expansion	27.819	12.580	40.399	15.239	14.203
Recession	16.884	15.286	32.170	1.597	19.704
H0: Expansion = Recession	***		*	*	*

Note: This table reports the magnitude of credit reallocation of bank loans for all non-financial firms, manufacturing firms and service firms. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Table 3: Magnitude of credit reallocation in different crisis periods (total debt)

All firms					
	POS	NEG	SUM	NET	EXC
Non-AFC	16.913	6.357	23.270	10.557	12.327
AFC (1998-2000)	16.143	3.166	19.309	12.976	6.333
Non-GFC	16.079	6.033	22.113	10.046	11.680
GFC (2008-2010)	24.205	6.294	30.499	17.911	12.588
Non-IFC	17.975	5.858	23.834	12.117	11.442
IFC (2016-2019)	8.902	7.452	16.354	1.450	14.022
Manufacturing					
	POS	NEG	SUM	NET	EXC
Non-AFC	16.211	6.427	22.638	9.784	11.761
AFC (1998-2000)	15.654	2.875	18.529	12.779	5.750
Non-GFC	15.316	6.213	21.529	9.103	11.333
GFC (2008-2010)	24.305	4.943	29.249	19.362	9.887
Non-IFC	17.148	5.280	11.868	22.428	10.159
IFC (2016-2019)	5.737	7.676	-1.938	13.413	11.475
Services					
	POS	NEG	SUM	NET	EXC
Non-AFC	20.859	5.585	26.444	15.274	8.980
AFC (1998-2000)	19.494	5.504	24.998	13.990	11.008

Non-GFC	20.414	5.127	25.541	15.287	9.424
GFC (2008-2010)	23.801	9.932	33.733	13.869	6.715
Non-IFC	21.793	5.891	27.685	15.902	9.557
IFC (2016-2019)	13.299	3.379	16.677	9.920	6.462

Note: This table reports the magnitude of credit reallocation of total debt for all non-financial firms, manufacturing firms and service firms during the different crisis period.

Table 4: Reallocation and productivity

Dependent Variable: Debt growth (Publicly traded firms)
Estimation method: Pooled OLS

	Model 1	Model 2	Model 3	Model 4
$\ln TFP_{t-1}$	0.010***	0.010***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
GDP_hp	0.028***	0.018***		
	(0.005)	(0.007)		
$\ln TFP_{t-1}$ * GDP_hp		-0.0007**		
		(0.0001)		
$\ln TFP_{t-1}$ * AFC			0.007	
			(0.008)	
$\ln TFP_{t-1}$ * GFC				0.006*
				(0.004)
AFC			0.074	
			(0.110)	
GFC				-0.175
				(0.522)
ROA_{t-1}	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
$Capital\_ratio_{t-1}$	0.004	0.004	0.004	0.004**
	(0.003)	(0.003)	(0.003)	(0.002)
$Sales\_growth_{t-1}$	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\ln Assets_{t-1}$	0.013***	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.191***	0.190***	0.190***	0.182
	(0.045)	(0.045)	(0.045)	(0.453)
Observations	11,357	11,357	11,357	11,357
R-squared	0.029	0.029	0.029	0.030
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5: Reallocation and productivity

Dependent Variable: Debt growth (Publicly traded firms)
Estimation method: Fixed effect

	Model 1	Model 2	Model 3	Model 4
$\ln TFP_{t-1}$	0.028***	0.028***	0.028***	0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
GDP_hp	0.009*	0.001		
	(0.005)	(0.007)		
$\ln TFP_{t-1}$ * GDP_hp		-0.0006*		

		(0.0001)		
$\ln TFP_{t-1}$ * AFC			-0.002	
			(0.010)	
$\ln TFP_{t-1}$ * GFC				0.002
				(0.004)
AFC			0.003	
			(0.130)	
GFC				-0.055
				(0.059)
Constant	0.841***	0.841***	0.841***	0.838***
	(0.091)	(0.091)	(0.091)	(0.092)
Observations	11,357	11,357	11,357	11,357
R-squared	0.029	0.029	0.029	0.030
Control	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: Reallocation and productivity (sub-sample analysis)

Dependent Variable: Debt growth
Estimation method: Pooled OLS

	Overall	**1991-2007**	**2008-2020**
$\ln TFP_{t-1}$	0.009***	0.023***	0.005**
	(0.002)	(0.003)	(0.002)
GDP_hp	0.0185***	-0.108	-0.002
	(0.007)	(0.117)	(0.006)
$\ln TFP_{t-1}$ * GDP_hp	-0.001**	0.003**	-0.001
	0.001	(0.002)	(0.000)
Constant	0.191***	0.179**	-0.006
	(0.045)	(0.077)	(0.038)
Observations	11,357	3,513	7,331
R-squared	0.029	0.072	0.018
Control	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Reallocation and productivity

Dependent Variable: Debt growth (Manufacturing sector)
Estimation method: Pooled OLS

	Model 1	**Model 2**	**Model 3**	**Model 4**
$\ln TFP_{t-1}$	0.013***	0.013***	0.014***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
GDP_hp	0.022***	0.012		
	(0.005)	(0.050)		
$\ln TFP\_{t-1}$ * GDP_hp		-0.001*		

		(0.001)		
$\ln TFP_{t-1}$ * AFC			-0.015	
			(0.027)	
$\ln TFP_{t-1}$ * GFC				0.019**
				(0.008)
AFC			-0.168	
			(0.393)	
GFC				-0.052
				(0.508)
Constant	0.178***	0.178	0.178	0.165
	(0.050)	(0.440)	(0.440)	(0.440)
Observations	9,954	9,954	9,954	9,954
R-squared	0.031	0.032	0.032	0.032
Control	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8: Reallocation and productivity

Dependent Variable: Debt growth (Service sector)
Estimation method: Pooled OLS

	Model 1	**Model 2**	**Model 3**	**Model 4**
$\ln TFP_{t-1}$	0.007*	0.007*	0.008*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
GDP_hp	-0.101**	-0.093*		
	(0.051)	(0.053)		
$\ln TFP_{t-1}$ * GDP_hp		0.001		
		(0.001)		
$\ln TFP_{t-1}$ * AFC			-0.016	
			(0.018)	
$\ln TFP_{t-1}$ * GFC				0.001
				(0.010)
AFC			0.402	
			(0.392)	
GFC				0.677
				(0.537)
Constant	-0.718	-0.725	-0.725	-0.719
	(0.447)	(0.449)	(0.450)	(0.447)
Observations	921	921	921	921
R-squared	0.050	0.050	0.051	0.050
Control	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9: Reallocation and productivity (Indian financial crisis)

Dependent Variable: Debt growth **Estimation method: Pooled OLS**			
	Overall	**Manuf.**	**Services**
$\ln TFP_{t-1}$	0.013***	0.022***	0.009*
	(0.002)	(0.004)	(0.005)
$\ln TFP_{t-1}$ * IFC	-0.010***	-0.029***	-0.007
	(0.003)	(0.007)	(0.007)
GDP_hp	0.026	0.026***	-0.088
	(0.052)	(0.010)	(0.054)
IFC	-0.368	-0.390***	0.790
	(0.550)	(0.076)	(0.559)
Constant	0.217	0.224***	-0.720
	(0.453)	(0.051)	(0.453)
Observations	11,357	9,954	921
R-squared	0.030	0.034	0.051
Control	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10: Reallocation and productivity (firms' leverage)

Dependent Variable: Debt growth **Estimation method: Pooled OLS**				
	High leverage		**Low leverage**	
	Model 1	Model 2	Model 1	Model 2
$\ln TFP_{t-1}$	0.005***	0.005***	0.015**	0.013*
	(0.002)	(0.002)	(0.007)	(0.007)
GDP_hp	0.013	0.014**	-0.103	-0.127***
	(0.021)	(0.007)	(0.064)	(0.017)
$\ln TFP_{t-1}$ * GDP_hp		0.0001		-0.003*
		(0.000)		(0.002)
Constant	0.094	0.094*	-0.986	-0.965***
	(0.205)	(0.052)	(0.633)	(0.108)
Observations	2,063	2,063	1,724	1,724
R-squared	0.166	0.166	0.029	0.031
Control	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, *p<0.1