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SAKAI, Koji
Kyoto Sangyo University

UESUGI, Iichiro
RIETI

Research Institute of Economy, Trade & Industry, IAA
The Research Institute of Economy, Trade and Industry
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The Extent and Efficiency of Credit Reallocation during Economic Downturns[1]

Koji Sakai[2] and Iichiro Uesugi[3,4,*]

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Abstract

The extant theoretical literature on credit reallocation yields conflicting predictions on both the extent and the efficiency of reallocation during economic downturns. Using a comprehensive dataset of Japanese firms of all sizes spanning a period of more than 30 years, including the period of prolonged economic stagnation in the 1990s called "Japan's Lost Decade," we examine which predictions are consistent with the data to find the following: (1) the extent of credit reallocation is smaller in recessions than in expansions, which is attributable to the decreasing extent of credit creation; (2) this tendency was more pronounced during the Lost Decade, especially for small firms that experience a significant drop in the extent of both credit creation and destruction; and (3) credit reallocation generally is efficiency-enhancing, but it is less efficiency-enhancing in recessions and became efficiency-reducing during the Lost Decade, possibly due to financial assistance by banks to large but low-quality firms (e.g., through evergreening). These findings together suggest that the inefficient credit reallocation during the Lost Decade was characterized by efficiency-reducing reallocation for large firms and a low level of aggregate reallocation for small firms.

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[2] Kyoto Sangyo University; Address: Motoyama Kamigamo Kita-ku, Kyoto, 603-8047, JAPAN; Email: ksakai@cc.kyoto-su.ac.jp.

[3] Hitotsubashi University; Address: 2-1 Naka-Kunitachi, Tokyo, 186-8603, JAPAN; Email: iuesugi@ier.hit-u.ac.jp; Phone: +81-42-580-8357; Fax: +81-42-580-8333.

[4] Research Institute of Economy, Trade and Industry, 1-3-1 Kasumigaseki, Chiyoda-ku, Tokyo, 100-8901, JAPAN.

* Corresponding author. Email: iuesugi@ier.hit-u.ac.jp; Mailing address: Institute of Economic Research, Hitotsubashi University, 2-1 Naka-Kunitachi, Tokyo, 186-8603, JAPAN; Phone: +81-42-580-8357; Fax: +81-42-580-8333.

1. Introduction

The interfirm allocation of physical and financial inputs for production, such as labor, capital, and external finance, is as important for the performance and efficiency of an economy as the sheer amount of these inputs. This has motivated many economists to construct aggregate measures for input reallocation and to examine the link between the extent of input reallocation and the business cycle. They first focused on the reallocation of jobs and physical capital across firms (Davis and Haltiwanger, 1992; Davis, Haltiwanger, and Schuh, 1996; Ramey and Shapiro, 1998; Eisfeldt and Rampini, 2006). Economists then turned to the reallocation of external financial resources, led by the seminal study by Herrera, Kolar, and Minetti (2011), which examines the extent and cyclicality of credit reallocation of large firms in the United States.[5] This was followed by Herrera, Kolar, and Minetti's (2014) study on the impact of credit reallocation on US economic growth and Hyun and Minetti's (2019) study on credit reallocation in Korea before and after the country's financial crisis in 1997.

Turning from empirical to theoretical research on the reallocation of resources, studies have arrived at conflicting predictions in several respects, including the extent, cyclicality, and efficiency of resource reallocation. For example, Caballero and Hammour (1994) and den Haan, Ramey, and Watson (2003) suggest that the extent of reallocation increases when the economy is in a downturn, while Caballero and Hammour (2005) and Chamley and Rochon (2011) argue the opposite and predict that the extent of reallocation will be smaller in a recession. Another respect in which studies yield conflicting predictions is with regard to the degree to which reallocation is efficiency-enhancing at different stages of the business cycle. Becsi, Li, and Wang (2005) argue that efficiency-enhancing reallocation is more pronounced during economic downturns, while Barlevy (2003) predicts that reallocation will actually be efficiency-reducing

[5] Note that there is also a strand of studies that examine credit reallocation among banks rather than among firms using bank-level information (Dell'Ariccia and Garibaldi, 2005; Contessi and Francis, 2013).

in recessions.[6] Yet, despite this lack of consensus, empirical research on the reallocation of resources – including research on the reallocation of credit – has tended to focus on discovering solid statistical regularities rather than on examining which of the conflicting theoretical views is supported by the data.

Against this background, the aim of this study is to empirically test hypotheses on the extent and efficiency of credit reallocation during economic downturns in Japan. To test these hypotheses, we construct measures of credit reallocation for firms of all sizes in Japan covering the period 1980–2014 and investigate the extent of credit reallocation, especially during periods of economic contraction. We then examine if this credit reallocation is efficiency-enhancing in that credit generally flows from low-productivity to high-productivity firms and if the extent of efficiency-enhancing reallocation in recessionary times differs from normal times. We employ quarterly financial statements data for both large firms and small and medium-sized enterprises (SMEs) spanning a period of more than 30 years.

Japan is an especially interesting laboratory for researchers to empirically test these hypotheses on credit reallocation for the following two reasons. First, it is a country where debt financing plays a much more important role than in the United States and an academic assessment of credit reallocation may hold important lessons for other countries in which debt financing plays a relevant role. However, to date, there are no studies on credit reallocation in Japan. Second, although there is an abundant literature on the role of debt financing in Japan, especially debt financing provided by banks, there is a paucity of studies offering a comprehensive data-based analysis of how well it has worked, covering a substantial period of time. Before the mid-1990s, many studies highlighted the positive aspects of the so-called main bank system, in which banks effectively channeled debt to large firms (Hoshi, Kashyap, and

[6] All of these theoretical studies on resource reallocation focus on economic downturns. The focus on and interest in economic downturns among researchers date back to Schumpeter (1934), who argued that the main function of recessions lies in the liquidation and reallocation of resources.

Scharfstein, 1990, 1991; Aoki, Patrick, and Sheard, 1994; Sheard, 1994). Then came the period that Hayashi and Prescott (2002), among others, labeled "Japan's Lost Decade," a period of prolonged stagnation in the 1990s following the collapse of asset price bubble. Many studies during and after the Lost Decade have pointed to the negative aspects, showing, for example, that distorted incentives for banks not to disclose massive loan losses motivated them to evergreen loans to unprofitable firms or that banks' financial assistance to nonviable firms had a negative impact on productivity in the economy overall (Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008). However, the literature on Japanese firm financing to date lacks research that covers the entire period, including the period before the Lost Decade, the Lost Decade of the 1990s itself, and the period since the Lost Decade. Moreover, there are few studies that include both large and small firms when examining how well debt financing has been working overall.

Our analysis yields the following three major findings. First, the extent of credit reallocation is smaller in recessions than in expansions, which is attributable to the decreasing extent of credit creation. Second, this tendency was more pronounced during the Lost Decade, especially for small firms, which experienced a significant drop in the extent of both credit creation and destruction. Third, credit reallocation generally is efficiency-enhancing, but it is less efficiency-enhancing in recessions and became efficiency-reducing during the Lost Decade, possibly due to financial assistance by banks to large but low-quality firms. These findings together suggest that the inefficient credit reallocation during the Lost Decade was characterized by efficiency-reducing reallocation for large firms and a low level of aggregate reallocation for small firms.

Our study contributes to the literature in three respects. First, this is the first study to construct credit reallocation measures for both large firms and SMEs and examine credit reallocation in the entire firm sector of a country. Our measures therefore allow us to compare the extent of, and fluctuations in, credit reallocation across firms of different sizes.

Second, we employ total factor productivity (TFP) at the firm level to examine the relationship between credit reallocation and productivity to see whether reallocation is efficiency-enhancing or efficiency-reducing, that is, whether credit flows from low-productivity to high-productivity firms or the other way around. Further, we also examine whether the efficiency-enhancing nature of reallocation is more pronounced or dampened during economic downturns, and if so, how.

Third, we shed new light on the efficiency of the Japanese loan market from a long-term perspective. While the Lost Decade of the 1990s, which saw the emergence of a severe financial crisis, has spawned a substantial body of literature, both empirical and theoretical, on how the crisis unfolded and affected the efficiency of the credit market (e.g., Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008; Chamley and Rochon, 2011; and Sakai, Uesugi, and Watanabe, 2010), our study examines a much longer time horizon. Specifically, we examine the efficiency of the market over more than three decades, while most preceding studies only cover the 1990s and the early 2000s, including the period of the Japanese financial crisis at the end to of the 1990s. Moreover, we study the efficiency of credit markets for firms of all sizes, whereas previous studies focus solely on large firms (e.g., Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008) or SMEs (e.g., Sakai, Uesugi, and Watanabe, 2010). Our analysis therefore is able to provide a broader perspective of the efficiency of the financial market not only in crises but also in normal times. Further, there have been a number of studies that examine credit market efficiency in countries other than Japan, especially after the 2007–2008 global financial crisis (e.g., Iyer et al., 2014; Sette and Gobbi, 2015; Beck et al., 2018; and Banerjee and Hofmann, 2018). Since these studies adopt the approaches employed by Peek and Rosengren (2005) and Caballero, Hoshi, and Kashyap (2008), our study provides results that allow comparisons with these studies.

The study proceeds as follows. Section 2 describes the previous literature and provides empirical hypotheses. Section 3 explains our data and several key variables, while Section 4 details the empirical approach we employ for the analysis. Sections 5 and 6 present the results, with Section 5 discussing the extent of credit reallocation during economic downturns and Section 6 focusing on the efficiency of reallocation. Finally, Section 7 concludes.

2. Previous literature and hypotheses[7]

2.1. Size of reallocation during economic downturns

Research on the reallocation of resources for production, such as labor, capital, and credit, focuses on two distinct but interrelated aspects: the creation of new production arrangements, and the destruction of obsolete arrangements. One of the primary objectives of studies on resource reallocation is to examine what happens when there is a negative shock to the economy – that is, how the creation and destruction of production arrangements are affected during an economic downturn.

One of the earliest theoretical studies on resource reallocation is that by Caballero and Hammour (1994), which examines the responses of the creation and destruction of production arrangements to cyclical variations in demand. Assuming nonlinear adjustment costs, they argue that the structure of creation costs gives industries a motive for smoothing the creation process and accommodate fluctuations in demand primarily through the destruction of production units. They therefore predict that reallocation will be more sizeable during economic downturns than during booms and that most of this reallocation is driven by the increase in the destruction of production units. Den Haan, Ramey, and Watson (2003) present a dynamic equilibrium model of the credit market that focuses on the role of matches formed by lenders

[7] For a more detailed review of the literature, please see the working paper version of this study (Sakai and Uesugi, 2020).

and entrepreneurs. In their model, the extent to which relationships between lenders and entrepreneurs break up is larger during recessions, resulting in greater credit reallocation. On the other hand, credit creation responds only slowly and makes only a relatively minor contribution to the change in credit reallocation.

These studies point to the possibility that, on the one hand, the extent of destruction of jobs, capital, and credit increases in recessions, leading to an increase in resource reallocation. On the other hand, the extent to which these productive resources are created decreases in recessions or remains stable at best. Summarizing the above discussion and focusing on the reallocation of credit, we posit the following hypothesis:

H1: The extent of credit reallocation becomes larger during economic downturns, driven by an increase in the extent of credit destruction.

Empirical evidence for an increase in credit destruction during recessions is provided by Herrera, Kolar, and Minetti (2011, Table 4) for the US and Hyun and Minetti (2019, Figure 2) for Korea. However, in Japan, where bank-firm relationships last much longer than in other countries, destruction of credit during economic downturns might not be as severe as elsewhere.[8]

We therefore also consider an alternative to Hypothesis 1 based on the theoretical study by Chamley and Rochon (2011), which predicts that bank-firm relationships continue to last during downturns. Specifically, focusing on the reallocation of credit, Chamley and Rochon (2011) employ a search and matching model of the credit market in which banks choose between short-term and long-term loans. In recessions, when the profitability of new loans

[8] For evidence regarding the duration of firm-bank relationships in Japan, among other countries, see Table 4.1 in Degryse, Kim, and Ongena (2009).

decreases and verification costs for projects financed through long-term loans increases, banks choose to roll over loans. Such behavior of banks will result in a lower level of credit destruction and creation and a smaller extent of credit reallocation. This argument can be summarized in the following hypothesis:

H1': Alternatively, the extent of credit reallocation becomes smaller during economic downturns. The extent of both credit destruction and creation remains stable or decreases.

2.2. Existence and extent of efficiency-enhancing resource reallocation

Another important objective of studies on resource reallocation is to examine if it is efficiency-enhancing, that is, if resources flow from the least productive to the most productive units. Many of the studies referred to in the previous subsection, including the study by Caballero and Hammour (1994), assume that reallocation is efficiency-enhancing. In their setups, only the most efficient production units participate in the production process. If the number of production units is insufficient, other production units enter the market based on a strict productivity ranking. By the same logic, if the number is excessive, the least efficient units go out of business. Applying their assumptions to the reallocation of credit, these studies yield the following hypothesis:

H2: Credit reallocation is efficiency-enhancing, that is, high-productivity firms are more likely to receive more credit and less likely to receive less credit than are low-productivity firms.

The extent to which reallocation is efficiency-enhancing may change during economic downturns. Some studies argue that the extent may increase during a downturn in that a larger amount of resources flows from low-quality to high-quality firms during a recession than normal times. Becsi, Li, and Wang (2005) develop a search and matching model for the provision of credit that incorporates heterogeneity in the quality of entrepreneurs (high-quality and low-quality). A negative shock leading to a recession has a disproportionately adverse impact on low-quality firms, leading to a breakup of existing matches these firms have with lenders. Thus, there will be a wider gap in credit availability between low-productivity and high-productivity firms during a downturn. The above argument yields the following hypothesis:

H3: The extent of efficiency-enhancing credit reallocation is more pronounced during economic downturns.

In contrast, other studies yield the opposite prediction of Hypothesis 3 and suggest that reallocation is less efficiency-enhancing or even efficiency-reducing during a downturn. In a state of less efficiency-enhancing reallocation, a larger number of unprofitable and nonviable production units remain in the market than in normal times, but exit and survival of production units is still based on the order of their productivity. In a state of efficiency-reducing reallocation, the productivity order for reallocation is reversed, that is, low-productivity firms are more likely to receive more credit than are high-productivity firms.

Such predictions are based on two lines of reasoning. The first focuses on severer frictions in the market for resources used for production. Caballero and Hammour (2005) incorporate frictions in the labor and/or credit market into their model to show that resource reallocation may be less efficiency-enhancing or efficiency-reducing. They call these situations "sclerosis" and "scrambling," respectively. A possible reason for such scrambling could be that, as highlighted by Barlevy (2003), the presence of credit market frictions may direct resources from more efficient to less efficient uses. Since, in practice, small firms are more likely to be financially constrained than large firms, we expect that this line of reasoning applies more to firms that are small in size.[9]

The second line of reasoning focuses on lenders' incentives and argues that lenders provide financial assistance to unproductive and nonviable firms in recessions and try to evergreen loans to these firms. Such behavior leads to less efficiency-enhancing or efficiency-reducing credit reallocation during economic downturns. Dewatripont and Maskin (1995) and Berglof and Roland (1997), for example, make this point couching their analyses in terms of a dynamic commitment problem for lenders. In the presence of sunk costs for prior investment, lenders find it profitable ex post to refinance firms with ex ante unprofitable projects.[10] Note that the above argument is more likely to hold for large loans if transaction costs for refinancing are fixed and minor relative to the benefits from evergreening these large loans. Fukuda, Kasuya, and Nakajima (2007) present other reasons for loan evergreening than the problem of dynamic commitment, including the difficulty of coordination among lenders and the political costs of liquidating too-big-to-fail firms. These issues are more serious in the case of loans to large firms than small firms. Further, several empirical studies find evidence for the evergreening of loans to large listed firms (Peek and Rosengren, 2005; Hoshi and Kashyap, 2004), while others argue that banks extend these loans to small businesses only occasionally (Fukuda, Kasuya, and Nakajima, 2007). The arguments presented in the above discussion are summarized in the following alternative hypothesis on the efficiency of credit reallocation in a downturn:

H3': Alternatively, credit reallocation becomes less efficiency-enhancing and may even become efficiency-reducing during a downturn. If financial constraints play a role, the tendency of

[9] In a similar vein, this logic applies to firms with high leverage. In later analyses, we focus not only to small firms but also firms with low capital ratios to examine Hypothesis 3'.

[10] Meanwhile, Bruche and Llobet (2014) argue that lenders' limited liability may lead to possible distortions in the credit market, which result in lenders providing financial assistance to nonviable borrowers in recessionary times.

reallocation being less efficiency-enhancing will be more pronounced for small firms, while it will be more pronounced for large firms if dynamic commitment or the too-big-to-fail issue matters for lenders.

In the sections that follow we examine which of these hypotheses are consistent with the data. We do this by employing data on firm financing in Japan for more than three decades from 1980 to 2014.

3. Data

This section describes the dataset and major variables we employ for our analysis. Specifically, we present details of our data sources and then explain how we measure credit reallocation.

3.1. Data sources

The main data source for our analysis is the *Quarterly Financial Statements Statistics of Corporations by Industry* (QFSSC) published by the Ministry of Finance of the Japanese government. An additional data source is the *Japan Industrial Productivity* (JIP) database for industry-level deflators and average working hours, which we use to construct our firm-level productivity variable (TFP).[11] The QFSSC are a survey of business corporations with paid-in capital of at least 10 million yen headquartered in Japan. The QFSSC contain information on firms' balance sheets, employment, industry, geographic location, etc., and cover all industries in both the manufacturing and the non-manufacturing sector, although we exclude the financial and insurance industry from the analysis.[12] The QFSSC comprise two parts: a part that targets all large corporations, and a part that consists of a sample of smaller firms. For the latter part,

[11] The JIP database has been produced by RIETI in collaboration with the Institute of Economic Research, Hitotsubashi University. For details, see https://www.rieti.go.jp/en/database/jip.html.

[12] We do so because the QFSSC have covered this industry only for a limited period (since the first quarter of fiscal 2008).

firms are randomly chosen and given questionnaires for four to eight quarters (one to two years). Throughout the analysis, we set the paid-in capital threshold value to distinguish large firms and SMEs to 100 million yen, following the criterion set by the Ministry of Finance. Details about what firms are chosen for the first part and how smaller firms are sampled are provided in Appendix A.

3.2. Construction of credit reallocation measures

To measure the extent of credit reallocation, we employ the approach of Davis and Haltiwanger (1992) and Herrera, Kolar, and Minetti (2011), using balance sheet information from the QFSSC. We denote by c_{ft} the average of firm *f*'s debt at time *t-1* and *t*. For the set of firms F_{st} belonging to sector *s*, we define C_{st} as the sum of c_{ft}. We define the time *t* debt growth rate of a firm, g_{ft}, as the first difference of its debt between time *t-1* and *t* divided by c_{ft}. This measure takes a value from -2 to +2.[13]

Further, we introduce two measures, credit creation and credit destruction. Credit creation is the sum of the debt growth rates of firms with increasing debt. For the set of firms F_{st} we calculate credit creation at time *t* (POS_{st}) as the weighted sum of the debt growth rates of firms with increasing debt. Similarly, credit destruction is the sum of the debt growth rates of firms with declining debt. Specifically, we calculate credit destruction at time *t* (NEG_{st}) as the weighted sum of the absolute values of the debt growth rates of firms with decreasing debt.

Using c_{ft}/C_{st} as weights, we define the measures for credit creation and destruction as follows:

$$POS_{st} = \sum_{\substack{f \in F_{st} \\ g_{ft} > 0}} \left(\frac{c_{ft}}{C_{st}}\right) g_{ft} \tag{1}$$

[13] Note that we have $g_{ft} = 0$ when the firm has zero debt outstanding at both time *t-1* and *t*.

$$NEG_{st} = \sum_{\substack{f \in F_{st} \\ g_{ft} < 0}} \left(\frac{c_{ft}}{C_{st}}\right) |g_{ft}| \tag{2}$$

We define credit reallocation at time t (SUM_{st}) as the sum of credit creation and credit destruction, which represents the magnitude of the reshuffling of credit among firms,

$$SUM_{st} = POS_{st} + NEG_{st}. \tag{3}$$

In addition, we also define the net change in credit at time t (NET_{st}), which is the difference between credit creation (POS_{st}) and credit destruction (NEG_{st}):

$$NET_{st} = POS_{st} - NEG_{st}. \tag{4}$$

We define another measure of credit reallocation, which we call "excess credit reallocation" (EXC_{st}), as the difference between credit reallocation (SUM_{st}) and the absolute value of net credit growth (NET_{st}), that is,

$$EXC_{st} = SUM_{st} - |NET_{st}|. \tag{5}$$

A net increase in credit can be achieved through positive credit creation and no credit destruction. Alternatively, a net credit decrease can be achieved through positive credit destruction and no credit creation. Hence, EXC_{st} measures credit reallocation in excess of the minimum required for net credit changes.

To construct our measures of credit reallocation, we could employ a number of different variables, namely, interest-bearing debt, loans from financial institutions, short-term loans from financial institutions, long-term loans from financial institutions, and corporate bonds. The variable that we mainly focus on in our analysis is interest-bearing debt, since it is the most comprehensive indicator of firms' debt financing, as it includes all the other four variables. We also employ loans from financial institutions in some analyses as some parts of the hypotheses are constructed based on theories on the behavior of financial institutions.

Three additional comments regarding details and the validity of the credit reallocation measures we construct are in order. First, we use firm-level information rather than contractlevel or project-level information for the credit reallocation measures. Firm-level information is suitable if a bank extends loans to a firm based on the firm's creditworthiness, while contract- or project-level information is suitable if a bank provides project financing based on the prospective profitability of an individual project implemented by the firm. Since a large part of our sample consists of small firms that are too small to implement multiple projects simultaneously, we think that it is more appropriate to use firm-level information.

Second, we focus on the reallocation among surviving firms rather than including entrant and exiting firms in our main analysis. This is due to the lack of information on firm entry and exit in the QFSSC. More specifically, we limit our calculation of g_{ft} to firms for which observations at both ends of the interval between time *t-1* and *t* are available and exclude new entrant and exiting firms for which no data are available at the beginning or end of the time interval. Excluding these entrant and exiting firms from the sample results in a downward bias in our reallocation measures POS_{st}, NEG_{st}, SUM_{st}, and EXC_{st}. In order to examine the extent of this bias, we conduct a supplementary analysis by matching the QFSSC with another firm-level data source that contains information on the timing of the entry and exit of firms. Appendix B details how we construct the dataset that includes information on firm entry and exit. The matched dataset covers only a limited time period, from 1999 to 2014, which is why we do not use it for our main analysis. It should further be noted that due to the lack of common identification codes, we cannot match all observations with the other data source. However, it is long enough to make it possible to compare the extent of credit reallocation taking firm entry and exit into account with the extent of credit reallocation in our main analysis focusing on surviving firms only.

Third, there are two potential ways to create aggregate credit reallocation measures for all firms (i.e., large firms and SMEs). The first would be to apply different weights to different groups of firms with different sampling ratios and response rates. The second would be to simply aggregate all firm observations without applying weights of any kind. We opt for the latter approach, since the Ministry of Finance does not provide official weights for the calculation of reallocation measures for all firm sizes. Note, however, that the reallocation measure for firms of all sizes is almost identical to that for large firms, since the sampling ratios for large firms are much larger than those for SMEs. Therefore, in order to avoid presenting almost duplicate results, we only present the results for large firms and SMEs in the main text.[14]

4. Empirical Approach

Having explained our data and the major variables employed for analysis, we now present the empirical procedure we employ to examine the hypotheses posited in Section 2.

4.1. Extent of credit reallocation in recessions

We use several approaches to examine credit reallocation during economic downturns to test Hypotheses 1 and 1'. The first approach is to simply aggregate the magnitude of credit creation and destruction to calculate the overall sum of reallocation and the extent of excess reallocation. We do this for periods of economic expansion and contraction and statistically examine if the extent of credit reallocation is larger in contractionary than in expansionary phases.

For this purpose, we need to identify periods of economic downturn. We employ two definitions of a downturn, covering different time spans. The first definition focuses on recessions that occur at a business cycle frequency and last for a relatively short period. Specifically, we use the dates of business cycle peaks and troughs officially reported by the Cabinet Office and define a recession as the period from a peak to a trough. During the period that our analysis focuses on (i.e., 1980 to 2014), there were seven recessions, each of which

[14] The results for firms of all sizes can be found in the working paper version of this study (Sakai and Uesugi, 2020).

was followed by an expansionary period.

Our second, alternative definition of a downturn focuses on a longer time span, and we regard Japan's decade-long economic stagnation during the 1990s as another type of economic downturn. Hayashi and Prescott (2002) described the 1990s as a "Lost Decade" for Japan – a prolonged period of economic stagnation characterized by substantially lower per capita output growth than previous decades. Reflecting this view, we define the Lost Decade in a way that is consistent with the short-term business cycle peaks and troughs identified by the Cabinet Office. Specifically, we regard the period from the business cycle peak at the beginning of the 1990s (FY1990 Q4) to the trough at the beginning of the 2000s (FY2001 Q4) as the period of a long-lasting economic downturn or Japan's Lost Decade.

This approach of measuring credit reallocation using the two definitions of a downturn is quite simple and straightforward. However, one drawback of this approach is that it fails to take into account, and make use of, differences in the depth of downturns in the analysis.

The second approach aims to overcome this drawback either by measuring correlation coefficients between one of the credit reallocation variables and an indicator for aggregate economic activity or by applying vector autoregression (VAR) to these variables.[15] For the VAR, we follow the procedure employed by Dell'Ariccia and Garibaldi (2005) and conduct reduced-form two-variable VARs with four lags. To represent aggregate economic activity, we employ two different variables: quarterly real GDP provided by the Cabinet Office, and the diffusion index (DI) for business conditions reported by the Bank of Japan on a quarterly basis.[16] We extract the cyclical components not only of the credit reallocation measures but

[15] Among the previous studies that examine the cyclicality of credit reallocation, Herrera, Kolar, and Minetti (2011), Dell'Ariccia and Garibaldi (2005), and Hyun and Minetti (2019) measured correlation coefficients, while Dell'Ariccia and Garibaldi (2005) adopted VAR. Note, however, that both of these methods examine the extent of reallocation when the economy is in a short-term recession and not when it is experiencing long-term stagnation.

[16] The DI is based on firms' responses in the Bank of Japan's *Tankan* survey regarding how they assess their current business conditions. The DI is obtained by subtracting the percentage of firms that say current conditions are unfavorable from the percentage of those saying that they are favorable, so that a higher DI

also of the real GDP series and use them as variables for our analysis. In contrast, we do not adjust the DI, since this is defined to move in a range between -100 and 100 and does not show any persistent upward or downward trend during the observation period.[17]

4.2. Existence and extent of efficiency-enhancing credit reallocation

Following the examination of Hypotheses 1 and 1', we focus on the existence and extent of efficiency-enhancing credit reallocation and test Hypotheses 2, 3, and 3'. To do so we examine the relationship between the reallocation of credit and productivity at the firm level. We start by examining Hypothesis 2 and employ a simple regression model connecting the growth rate of our debt variables and productivity. The baseline specification is given by the following equation:

$$g_{ft} = \alpha + \beta TFP_{ft-1} + \gamma Cycle_t + \theta X_{ft-1} + \xi Industry_i + \varepsilon_{ft}, \tag{6}$$

where g_{ft}, which we introduced in Section 3.2, is the first difference of the debt values of firm *f* between time *t-1* and *t* divided by the average amount of debt outstanding. We employ interest-bearing debt for the debt variable in the baseline and use loans from financial institutions as an alternative. TFP_{ft-1} is the level of firm *f*'s TFP at time *t-1*. We detail how we calculate firm-level TFP in Appendix C. $Cycle_t$ represents the state of the aggregate economy at time *t*. For $Cycle_t$, we use either the HP-filtered quarterly cyclical component of real GDP or the original

indicates better business conditions.

[17] More specifically, we follow Dell'Ariccia and Garibaldi (2005) in the way we extract the cyclical components. The cyclical component of each series is defined as the deviation of the logged original values of the credit reallocation measures and those of real GDP from their Hodrick-Prescott (HP) filtered logged values, with a smoothing parameter of 1,600 that business cycle studies usually employ for quarterly data. The cyclical component therefore is expressed in percentage terms. To ensure that the reallocation measures are expressed in percentage terms, we adjust the original values of the credit reallocation measures by multiplying them by C_{st}. Note that we do not derive cyclical components for the net credit change, since it may take negative values and cannot be logged.

series of the DI for business conditions. X_{ft-1} is a set of variables to control for firm characteristics. Variables include firm size as measured by the log of firms' assets, firms' internal cash flow as measured by operating profits standardized by total assets, firms' growth opportunities as proxied by the rate of sales growth, and firms' net worth as measured by the capital ratio. $Industry_i$ is a dummy for industry i that firm f belongs to. Since firms' productivity and other characteristics may be endogenously determined, we take a one-period lag of these explanatory variables, following Foster, Grim, and Haltiwanger (2016), who examine the impact of productivity on job reallocation.

We estimate this equation for the period from FY1980 Q1 to FY2013 Q4 by pooling all observations.[18] If Hypothesis 2 holds and there exists efficiency-enhancing reallocation in which credit moves from low-productivity to high-productivity firms, coefficient β will be positive.

Next, we try to test Hypotheses 3 and 3' by further examining the existence and extent of efficiency-enhancing credit reallocation during economic downturns. We employ two different approaches, reflecting the duration of the economic downturn(s) we consider. First, we focus on downturns that occur at a high frequency and examine how the extent of efficiency-improving reallocation changes during these downturns. More specifically, we add an interaction term between TFP and the state of aggregate economic conditions to equation (6):

$$g_{ft} = \alpha + \beta TFP_{ft-1} + \gamma Cycle_t + \delta TFP_{ft-1} \times Cycle_t + \theta X_{ft-1} + \xi Industry_i + \varepsilon_{ft} \quad (7)$$

If Hypothesis 3 holds, δ should be negative, while it should be positive if Hypothesis 3' is correct. Further, in the case that Hypothesis 3' holds true, we call the reallocation efficiency-

[18] We limit the observation period to the end of fiscal 2013 rather than the first quarter of 2014, which is the last period of our credit reallocation data, because some of the data we need for the calculation of our variables from the JIP database are unavailable.

reducing when $\beta + \delta Cycle_t$ becomes negative.

Second, we examine the extent of efficiency-enhancing reallocation during the period of long-term economic stagnation. For this purpose, we estimate equation (6) for different observation periods. Specifically, we divide the overall observation period into three sub-periods; namely, before the Lost Decade, the Lost Decade, and after the Lost Decade. Thus, we estimate the following three equations:

$g_{ft} = \alpha_1 + \beta_1 TFP_{ft-1} + \gamma_1 Cycle_t + \theta_1 X_{ft-1} + \xi_1 Industry_i + \varepsilon_{1ft}$ if t is before the Lost Decade;

$g_{ft} = \alpha_2 + \beta_2 TFP_{ft-1} + \gamma_2 Cycle_t + \theta_2 X_{ft-1} + \xi_2 Industry_i + \varepsilon_{2ft}$ if t is during the Lost Decade;

$g_{ft} = \alpha_3 + \beta_3 TFP_{ft-1} + \gamma_3 Cycle_t + \theta_3 X_{ft-1} + \xi_3 Industry_i + \varepsilon_{3ft}$ if t is after the Lost Decade. (8)

If Hypothesis 3 holds, β_2 should be larger than β_1 and β_3, while the opposite should be the case if Hypothesis 3' holds. In the case that Hypothesis 3' holds, reallocation is efficiency-reducing when β_2 is negative.

5. Results for the extent of credit reallocation

In the following two sections we examine if the hypotheses posited in Section 2 are consistent with the data by employing the empirical approach presented in Section 4. In this section, we examine Hypotheses 1 and 1' on the extent of reallocation during economic downturns.

5.1. Extent of credit reallocation during economic downturns

We start by graphically depicting developments in reallocation for interest-bearing debt over the observation period in Figure 1 to capture the overall trend in credit reallocation in Japan. There are two notable features. First, in the late 1980s, the level of POS was much higher than in other periods. It was also substantially higher than that of NEG in the same period. As a result, SUM, EXC, and NET reached their highest level during the entire observation period. Then, following the collapse of the asset price bubble in the early 1990s, all five reallocation measures dropped dramatically in the subsequent recession. Second, from the start of the Lost Decade in the early 1990s to the mid-2000s, POS remained stable at a low level, while NEG gradually increased both for large firms and SMEs. As a result, SUM, EXC, and NET were driven by the increase in NEG rather than by changes in POS during the period, with SUM increasing, EXC being rather stable, and NET decreasing in a gradual manner.

Next, we examine how the five reallocation measures for debt instruments differ depending on the state of the economy. Table 1 presents the result for the comparison between short-term recessions and expansions and the result for the comparison between the three subperiods – before, during, and after the Lost Decade. In panel (a), we focus on interest-bearing debt. Two notable features stand out. First, for large firms, there are several measures that significantly differ between expansionary and recessionary periods. Specifically, NET is significantly larger and NEG and EXC are significantly smaller during recessionary periods than during expansionary periods. Qualitatively similar results are found for SMEs, but the differences between recessionary and expansionary periods are smaller and less significant.

Second, focusing on longer periods, we find that for both large firms and SMEs, with the exception of NEG for large firms, all the reallocation measures are significantly smaller for the Lost Decade than for the periods before and after the Lost Decade taken together. The difference between the Lost Decade and the periods before and after the Lost Decade is more pronounced for SMEs than for large firms.

In panel (b), we implement the same set of comparisons using an alternative debt measure of bank loans, because some parts of Hypotheses 1 and 1' are based specifically on banks' behavior of lending to borrower firms. The results confirm, and are even more clear-cut than, the findings from panel (a). First, when we focus on large firms in short-term recessions, the NEG, SUM, and EXC are significantly smaller in recessions than in expansions, while only NEG and EXC become significantly smaller when we employ interest-bearing debt. In contrast, there is no substantial change in the statistical significance for SMEs in short-term recessions from the result we obtained for interest-bearing debt. Second, for large firms in the long-term economic downturn of the Lost Decade, the margins of decrease in POS and SUM in the Lost Decade become more sizable and the sign of the difference between the Lost Decade and the non-Lost Decade turns negative. Similarly, we observe a slightly larger extent of decline in POS, SUM, and EXC for SMEs during the Lost Decade.

Overall, our results in this subsection indicate that the extent of reallocation as measured by EXC or SUM is smaller in short-term recessions than in expansions and that this is largely driven by the smaller NEG in recessionary periods. This finding of a smaller extent of credit destruction and reallocation in recessions is inconsistent with Hypothesis 1 but consistent with Hypothesis 1'. We regard this as a unique feature of debt financing in Japan when compared with findings for the US and Korea that indicate a substantial increase in credit destruction in recessions. Further, examining the extent of reallocation during the long-term economic downturn, the results favor Hypothesis 1' over Hypothesis 1. Both SUM and EXC are significantly smaller for the Lost Decade than the periods before and after the Lost Decade, which is attributable both to the decrease in POS for both large firms and SMEs and to the decrease in NEG for SMEs.

Lastly, before we move on to the next subsection, we briefly consider the extent to which the above results may change when firms that newly entered or exited the market are included. As mentioned above, data that allow us to include entering and exiting firms and cover the entire period are not available. Using a more limited dataset including entering and exiting firms but covering only the period from 1999 to 2014 (see Appendix B), we find that the signs on the differences between the reallocation measures in expansionary and recessionary periods are the same regardless of whether we include or exclude entering and exiting firms. We therefore conclude that ignoring firm entry and exit does not appear to substantially bias the results. The detailed results are provided in Appendix D.

5.2. Correlation between reallocation measures and economic conditions

Next, we estimate the correlation coefficients between the reallocation measures for interest-bearing debt and the aggregate economic indicators. Table 2 shows the correlation coefficients. We find that credit creation (POS) is procyclical for both large firms and SMEs and across different aggregate economic conditions. Specifically, while some of the contemporaneous and leading correlation coefficients are insignificant, the correlation coefficients between POS and all the lagged GDP and DI variables are statistically significant and positive. For credit destruction (NEG), no consistent signs on the correlation coefficients with lagged or leading GDP variables are observed: while the correlation coefficients are significantly positive for some of the leading GDP variables, for some of the lagged GDP variables they are significantly negative. In contrast, the correlation coefficients between NEG and DI that are significant are all positive.

Given that credit creation (POS) is procyclical while credit destruction (NEG) does not show a clear cyclical pattern, both credit reallocation (SUM) and excess reallocation (EXC) are positively correlated with some of the lagged, contemporaneous, and leading GDP and DI variables and hence also procyclical.

To summarize, the extent of credit reallocation (SUM) and of excess reallocation (EXC) is positively correlated with lagged values of aggregate economic conditions, indicating that the extent of credit reallocation is smaller during economic downturns than during expansionary phases. This is due mostly to the smaller extent of credit creation (POS) in recessions. While we find that the extent of credit destruction (NEG) becomes larger for large firms during downturns when we employ the real GDP variable, its impact on the overall extent of credit reallocation is limited.

5.3. Vector Autoregression

We employ VAR and measure the impact of negative aggregate shocks on the extent of credit reallocation for interest-bearing debt as another way to examine Hypotheses 1 and 1'. Starting with large firms, Figure 2 indicates that both when focusing on GDP and when focusing on DI, an adverse shock results in a decrease in the extent of credit reallocation: SUM and EXC both show a negative response that is statistically significant at the five percent level around five to ten quarters after an adverse shock. In addition, POS falls significantly for four to five quarters after a negative shock. In contrast, the response of NEG is not statistically significant.

Next, Figure 3 shows the corresponding results for SMEs. Overall, the responses of the reallocation measures are smaller than in the case of large firms. That is, while POS falls significantly in response to a negative shock to real GDP or the DI, the decline in SUM is significant only in the case of a negative shock to the DI, and all the other responses are not significant.[19]

Taken together, the results indicate that the extent of credit reallocation as measured by SUM or EXC decreases following a negative shock to the economy, and this decline is

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[19] Throughout the two subsections focusing on correlation coefficients and VAR, we follow the convention and extract cyclical components by applying the HP filter to credit reallocation and real GDP. Note, however, that the results become weaker when we instead employ raw values for the credit reallocation measures and real GDP without filtering and estimate the correlation coefficients and conduct VAR. The results when using the raw values are provided in Appendix E.

mostly driven by the drop in the extent of credit creation, i.e., POS. This is in line with Hypothesis 1', which predicts that the extent of reallocation and credit creation will be smaller in recessions. We also find that credit destruction does not play a significant role in either increasing or decreasing the extent of reallocation. This is inconsistent with Hypothesis 1, which predicts that credit destruction plays an important role during economic downturns.

6. Results for the Efficiency of Credit Reallocation

Having examined the extent of credit reallocation in the previous section, we examine in this section the efficiency of credit reallocation and test Hypotheses 2, 3, and 3'. We do so by focusing on the link between credit reallocation and firm-level productivity.

6.1. Summary statistics

Table 3 presents summary statistics of the variables used for analysis in this section. The dependent variable, debt growth, is the rate of change either in a firm's interest-bearing debt or in its loans from banks and ranges from -2 to +2. The average values are -0.0066 and -0.0098, respectively. This indicates that firms' total borrowing and bank loans decreased slightly over the course of our observation period. Regarding TFP, to get a sense of developments in the key explanatory variable, we look at the dispersion of TFP, which is one way to examine for the existence of resource misallocation (see, e.g., Hsieh and Klenow, 2009). Developments in the standard deviation of TFP are shown in Figure 4, which indicates that the dispersion of TFP increased during the period overall, especially from 1989 to 2003, which more or less corresponds to Japan's Lost Decade. Although there may be other reasons for the increasing dispersion of productivity, and the increase does not necessarily provide evidence for the presence of credit misallocation, the trend is consistent with the conjecture that Japan's economy suffers from a serious misallocation of resources, and that this problem intensified especially during the 1990s.[20]

As an initial attempt to relate the reallocation measures to productivity, we divide firms in the dataset in each quarter into quartiles based on their TFP level and calculate the extent of credit reallocation. The results, which are presented in Appendix Figure F-1, indicate that there is a substantial positive association between productivity and all the reallocation measures except for NET. However, while this analysis provides some first impressions on the possible link between the reallocation measures and productivity, it does not consider the extent of efficiency-enhancing reallocation among firms within each productivity quartile and does not control for other variables that potentially affect the extent of reallocation. The following subsection therefore presents a set of firm-level analyses on the relationship between productivity and credit reallocation.

6.2. Baseline estimation

We start with our baseline estimation, which employs equation (6) from Section 4.2. The results are shown in Table 4. The key variable of interest is $lnTFP_{t-1}$, the one-period lag of the natural log of TFP. In column (1) we find that the coefficient on $lnTFP_{t-1}$ is positive and significant, indicating that the growth rate of debt is larger for more productive than for less productive firms, which means that credit flows from low-productivity to high-productivity firms. This observation is consistent with Hypothesis 2 that credit reallocation is efficiency-enhancing. We obtain a somewhat different result when the DI instead of real GDP is used in the estimation: in column (2), the coefficient on $lnTFP_{t-1}$ turns insignificant.

Next, to investigate under what circumstances we find a significant positive coefficient on $lnTFP_{t-1}$, we conduct estimations employing equation (7), in which the interaction term

[20] Ito and Lechevalier (2009) find a similar tendency of an increasing TFP dispersion in Japan over the period 1994–2003. They attribute the increase to the internationalization of Japanese firms.

between TFP and the cyclical component of one of the two aggregate economic indicators (real GDP or the DI) is added. Columns (3) and (4) show the results, which differ somewhat from each other. In column (3), the coefficient on $lnTFP_{t-1}$ is positive and significant and the interaction term is not significant, while in column (4) both $lnTFP_{t-1}$ and the interaction term have positive and significant coefficients. Based on the result in column (4), we can say that reallocation is less efficiency-enhancing in economic downturns. The threshold value for the DI above which the impact of TFP on credit growth is positive is about -20 (=-0.00471/0.000239). Since three quarters of all observations in the dataset show a DI of no smaller than -24, we can say that in most cases credit reallocation is efficiency-enhancing, but it becomes efficiency-reducing for very small DI values.

From these results, we infer the following. First, generally speaking, productivity has a positive impact on the growth of credit, which is consistent with Hypothesis 2. Second, the positive impact becomes smaller in recessions when we employ the interaction term of TFP and the DI, indicating that reallocation is less efficiency-enhancing, and turns negative when the depth of the recession exceeds a certain threshold, indicating that it is efficiency-reducing. These results are consistent with Hypothesis 3' rather than Hypothesis 3. Note, however, that the evidence supporting Hypothesis 3' is not that strong since we find no evidence for the hypothesis when employ the interaction term of TFP and the cyclical component of GDP.

In order to further examine Hypotheses 3 and 3', we therefore look at the impact of Japan's long-term economic stagnation during the Lost Decade rather than the impact of short-term recessions. For the estimation, the results are shown in columns (5) to (10). Interestingly, the coefficients on $lnTFP_{t-1}$ differ substantially across the subperiods. For the period before the Lost Decade (i.e., the 1980s), the coefficients on $lnTFP_{t-1}$ are positive and significant, as shown in columns (5) and (6). In contrast, for the Lost Decade, the coefficients are significantly negative (columns (7) and (8)). Finally, for the period after the Lost Decade (columns (9) and

(10)), the coefficients become positive again but are smaller than before the Lost Decade. In sum, we find that credit reallocation was not only less efficiency-enhancing in the Lost Decade than in other periods but also efficiency-reducing. This finding is again consistent with Hypothesis 3' rather than Hypothesis 3.

It is worth having a brief look at the results for the other explanatory variables used as controls. They are generally consistent with expectations. The coefficients on $lnAssets_{t-1}$ are negative, while those on $Sales\_growth_{t-1}$ are positive, indicating that smaller and fast-growing firms tend to have a larger demand for funds. Next, the coefficients on firms' return on assets (ROA), which represents their profitability, are negative and significant. This simply reflects that profitable firms tend to have abundant internal financial resources to meet their needs and therefore are less likely to demand external funding. Finally, the coefficients on $Capital\_ratio_{t-1}$, which represents firms' creditworthiness and the agency costs they face, are positive and significant, indicating that firms with a high capital ratio are more likely to be able to obtain outside funding than firms with a low capital ratio.

Since some parts of Hypothesis 3' are about banks' lending behavior rather than about firms' financing overall, we also implement the same set of estimations using an alternative dependent variable of loans extended by banks. The results are shown in Table 5 and are similar to those in Table 4, although there are a few notable differences. For the entire period, the coefficients on $lnTFP_{t-1}$ are positive and larger than those in Table 4, indicating that the extent to which the reallocation of bank loans was efficiency-enhancing was more pronounced than the extent to which the reallocation of interest-bearing debt was efficiency-enhancing. In the subperiod analyses, the most notable difference from Table 4 is that the coefficients on productivity are insignificant for the Lost Decade but not significantly negative. We can therefore say that during the Lost Decade the reallocation of bank loans was less efficiency-enhancing than in other periods, but we cannot say that it was efficiency-reducing.

The result that the reallocation of bank loans was not efficiency-reducing but that the reallocation of interest-bearing debt was efficiency-reducing may contradict the contention in some previous studies (e.g., Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008) that Japanese banks followed perverse incentives to extend loans to nonviable firms during the Lost Decade. It could be that the reallocation of bank loans was efficiency-reducing only for a specific category of firms, an issue which we will examine in Section 6.4.

6.3. Estimations including exiting firms

In the baseline estimation, we limited our focus to surviving firms and excluded those that exited or entered during the observation period. However, credit reallocation for these entering and exiting firms may differ from that for surviving firms. In order to examine this issue, we implement an estimation that includes not only surviving but also exiting firms by employing the dataset we introduced in Section 3.2 and Appendix B to measure the extent of reallocation. Note that due to data limitations this estimation covers only a shorter period from 2000 to 2013 than the baseline estimation.

Table 6 shows the results. Columns (1) to (4) present the results of the estimations including exiting firms. The coefficients on $lnTFP_{t-1}$ are all positive and significant, supporting Hypothesis 2. Meanwhile, the coefficients on the interaction terms in columns (3) and (4) are not significant, meaning that we cannot say whether Hypothesis 3 or 3' is supported. Columns (5) to (8) show the estimation results for surviving firms only. The results are qualitatively quite similar to those in columns (1) to (4). That is, the coefficients on $lnTFP_{t-1}$ are all positive and significant and those on the interaction terms are all insignificant. In sum, including exiting firms in the dataset does not qualitatively change the estimation results or our assessment regarding which of the hypotheses are consistent with the data.

In order to further examine how the inclusion of exiting firms affects our results with regard to Hypothesis 2, we compare the productivity levels of surviving and exiting firms. If the productivity of surviving firms is higher than that of exiting ones, the process of firm survival and exit will increase the average productivity level, which would provide further supporting evidence for Hypothesis 2. Column (11) shows the results of *t*-tests for the difference between the means of explanatory variables for firms that survived and those that exited. The difference in average TFP between surviving and exiting firms is not statistically significant. This result, indicating that a decline in the amount of credit outstanding due to the exit of firms neither increases nor decreases average productivity, neither supports nor rejects Hypothesis 2.

6.4. Examination of the reasons for efficiency-reducing reallocation in the Lost Decade

The results in Tables 4 through 6 showed that credit reallocation is generally efficiency-enhancing; moreover, the extent to which reallocation is efficiency-enhancing is smaller in recessions, and reallocation was in fact efficiency-reducing during the Lost Decade. However, it is still unclear why reallocation was efficiency-reducing during the Lost Decade. As posited in the latter part of Hypothesis 3', there are two possible explanations, focusing on financial constraints on productive firms and financial assistance to unproductive and nonviable firms.

The first explanation is based on the conjecture that productive firms have a larger demand for loans than less productive firms and therefore are more likely to be financially constrained in a recession. Based on this line of reasoning, we predict that small or highly leveraged firms, which are more likely to be financially constrained in recessions, tend to experience efficiency-reducing credit reallocation. The second explanation focuses on firms that are likely to receive financial assistance when they are unproductive and nonviable. We predict that large firms, which are often too big to fail or cause a dynamic commitment problem for lenders, receive financial assistance and experience efficiency-reducing reallocation in economic downturns.

With these two potential explanations in mind, we estimate specification (9) for two different sets of subsamples: by firm size and capital ratio. If the first explanation holds, small firms or highly leveraged firms will have experienced efficiency-reducing credit reallocation during the Lost Decade, that is, we will observe a negative β_2 for these firms. In contrast, large firms will have experienced efficiency-reducing reallocation if the second explanation fits reality.

Figure 5 shows the results in four different panels, which present the coefficients on $lnTFP_{t-1}$ in the estimation for debt growth and bank loan growth during the Lost Decade. The left panels use debt growth as the dependent variable. The top left shows the coefficient estimates for three subsamples based on firm size, i.e., small, large, and very large firms. While the coefficient for very large firms is negative and significant, those for small and large firms are insignificant. This result is more consistent with the second explanation, based on which we predicted that it is very large firms – i.e., firms that are too big to fail or cause dynamic commitment problems for lenders – among which efficiency-reducing credit reallocation will be concentrated. Next, we divide firms into quartiles in terms of their capital ratio and conduct estimations for each subsample. The results are shown in the bottom left panel. Only in the estimation for firms in the third (i.e., second highest) quartile in terms of their capital ratio do we obtain a negative and significant coefficient, while the other three estimations yield insignificant coefficients. This is not consistent with the first explanation, which predicts a negative coefficient for firms with low a capital ratio. Finally, the panels on the right employ the growth of bank loans as the dependent variable and obtain qualitatively similar results as in the left panels.

The above results are consistent with the second explanation that financial institutions have tended to continue extending loans to financially assist unprofitable and nonviable firms. However, they still do not provide conclusive evidence that the financial assistance provided by banks during the Lost Decade was efficiency-reducing, as suggested by studies on zombie firms such as that by Caballero, Hoshi, and Kashyap (2008).

We therefore implement another subsample analysis for the Lost Decade that distinguishes between firms that received financial assistance and those that did not. We follow Caballero, Hoshi, and Kashyap to detect whether firms received financial assistance. Details of the procedure are provided in Appendix G.[21]

The results of this analysis are shown in Figure 6 and differ depending on whether overall debt (left panel) or bank loans (right panel) . The left panel shows that the coefficients for both firms that received financial assistance and those that did not are significantly negative and very similar in size. In contrast, in the right panel, the coefficients for the two groups of firms differ in that reallocation was efficiency-reducing for firms that received assistance, while it was neither efficiency-enhancing nor efficiency-reducing for firms that did not receive assistance. As the focus of the examination is on the assistance extended by financial institutions, what is of interest here is the result for bank loans. Based on this result, we can say that reallocation was efficiency-reducing when firms received financial assistance during the Lost Decade, providing support for the explanation based on the last sentence in Hypothesis 3'.

6.5 Discussion on the overall efficiency of firm financing in Japan

Thus far, we have examined if credit reallocation is efficiency-enhancing or efficiency-reducing based on the firm-level estimations in Section 6, while we measured the extent of aggregate credit reallocation in Section 5. We now relate the firm-level estimation results to the extent of aggregate reallocation and evaluate the efficiency of firm financing especially during the Lost

[21] Caballero, Hoshi, and Kashyap use this procedure for the purpose of detecting zombie firms. There are several other studies that provide different definitions of zombie firms including Fukuda and Nakamura (2011), Imai (2016) and Goto and Wilbur (2019). However, we solely employ the procedure by Caballero, Hoshi, and Kashyap because their definition is simply based on the difference between a firm's individual interest rate and the market prime rate, which is orthogonal to a change in a firm's borrowing amount.

Decade in the following manner. Suppose that reallocation is efficiency-enhancing in the firm-level estimations and that there is a large amount of credit creation (POS) and destruction (NEG), resulting in a large credit reallocation (SUM or EXC). Together, this means that the debt of a large number of productive firms increases substantially and, at the same time, the debt of a large number of unproductive firms decreases substantially. This leads to a substantial increase in average productivity in the firm sector. We regard this situation as efficient aggregate credit reallocation. In contrast, aggregate credit reallocation is not efficient if firm-level reallocation turns efficiency-reducing or if the extent of credit reallocation becomes smaller.

In order to graphically examine the efficiency of aggregate credit reallocation, Figure 7 plots the results of rolling regressions based on the procedures in the previous sections. Specifically, in the panels of the figure, the extent of credit reallocation is represented by the horizontal axis and the size of the coefficients on productivity in the firm-level reallocation estimations is represented by the vertical axis. Each pair of observations – consisting of the measure of the extent of credit reallocation and the coefficient estimate of the four-year rolling – is depicted by a blue dot, with the year representing the last year of the rolling regression window.

Figure 7 consists of three panels. The top panel that shows the results for firms of all sizes. In this panel, the dots for the period before the Lost Decade are all in the upper range of the observations on the vertical axis and generally in the middle or toward the right on the horizontal axis, suggesting that this period was characterized by efficiency-enhancing reallocation at the firm-level and by a large extent of aggregate reallocation. This combination implies that aggregate credit reallocation during the period was efficient. Moreover, within this period, the observations for 1989 and 1990 are farthest to the right, suggesting that this is when aggregate reallocation became the most efficient. Then came the Lost Decade, and the efficiency of aggregate credit reallocation deteriorated: the dots moved down to lower left and stayed around the zero line. Thus, the aggregate reallocation became less efficient as firm-level credit reallocation became less efficiency-enhancing and aggregate credit reallocation became smaller than in the preceding period. Finally, in the period after the Lost Decade, the efficiency of aggregate reallocation recovered but remained below the period before the Lost Decade. The dots are located below the zero line for the first few years but jumped up above the zero line in 2005. However, after the global financial crisis, the extent of credit reallocation declined again, so that the dots moved toward the left.

The two panels in the bottom of the figure present the efficiency of aggregate reallocation for large firms and SMEs, respectively. The pattern for large firms is similar to that for all firms, except that the vertical values and hence their changes are amplified, suggesting more substantial changes in the extent of efficiency-enhancing reallocation for these firms. In contrast, for SMEs range of values along the vertical axis, and hence their change, is much smaller than for firms of all sizes, but the range of values along the horizontal axis is substantially larger.

These results by firm size suggest that both large firms and SMEs experienced a substantial drop in the efficiency of credit reallocation, but in a different manner. Aggregate credit reallocation for large firms became inefficient in the sense that firm-level reallocation became efficiency-reducing, meaning that credit flowed from productive to unproductive firms. In contrast, for SMEs there was no substantial change in the extent of efficiency-enhancing reallocation at the firm level; however, the extent of aggregate credit reallocation to them shrank substantially during the period.

7. Conclusion

This study focused on the reallocation of credit in Japan across both large firms and SMEs spanning a period of more than three decades. We first examined the extent of credit reallocation, especially when the economy is in a downturn. We then investigated if reallocation is efficiency-enhancing, that is, if credit flows from less productive to more productive firms. We obtained the following three major findings. First, the extent of credit reallocation is smaller in recessions than in expansions, which is attributable to the decreasing extent of credit creation. Second, this tendency was more pronounced during the Lost Decade, especially for small firms that experience a significant drop in the extent of both credit creation and destruction. Third, credit reallocation generally is efficiency-enhancing, but it is less efficiency-enhancing in recessions and became efficiency-reducing during the Lost Decade, possibly due to financial assistance to large but low-quality firms. These findings together suggest that the inefficient credit reallocation during the Lost Decade was characterized by efficiency-reducing reallocation for large firms and a low level of aggregate reallocation for small firms.

While these results provide useful insights into the efficiency of credit reallocation in Japan, the research could be extended in a number of ways. For example, an examination of the interaction between the reallocation of interest-bearing liabilities and the reallocation of physical inputs (labor and capital) or of other financial resources (equity and internal funds) may provide further insights on the functioning of resource reallocation in the economy. Given that the amount of research on the reallocation of financial resources is still quite limited relative to the abundant literature on job and capital reallocation, an interesting avenue for future research would be to examine the substitutive and/or complementary relationships between the reallocation of different resources. Another important issue for future research is to examine what firms determine the extent and efficiency of credit reallocation. For example, the extent and efficiency of credit reallocation could be driven by the behavior of a limited number of large firms. Or it could be driven by highly levered firms (i.e. firms with negative net worth) or unlevered firms (i.e., firms that hold no debt during the period). There has been a growing interest in the latter type of firms (see, e.g., El Ghoul et al., 2018), and the share of such unlevered firms has been on the rise in Japan in recent years. It would be interesting to examine the role of such firms in the context of credit reallocation.[22]

[22] In Appeidix H we show the development of zero-leverage firms in Japan during the period of analysis. We also present the development of negative net worth firms during the same period in order to examine the extent firms with low leverage and those with high leverage coexist in the market.

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Table 1: Extent of reallocation for interest-bearing debt and bank loans in different periods

This table reports the extent of credit reallocation of interest-bearing debt and bank loans and compares each of the reallocation measures between different periods. Definitions of variables are provided in Section 3.2. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

(a) Interest-bearing debt	Large firms					SMEs				
	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Entire period	0.038	0.032	0.006	0.069	0.052	0.047	0.040	0.007	0.086	0.070
Expansions	0.037	0.033	0.004	0.071	0.054	0.046	0.041	0.005	0.086	0.070
Recessions	0.038	0.029	0.010	0.067	0.049	0.048	0.038	0.010	0.087	0.070
H0: Expansions = Recessions		***	***		**		*	*		
Not Lost Decade	0.040	0.031	0.009	0.071	0.054	0.051	0.043	0.008	0.094	0.075
Lost Decade	0.032	0.033	0.000	0.065	0.048	0.037	0.034	0.003	0.071	0.059
H0: Lost Decade = Not-Lost Decade	***		***	***	***	***	***	**	***	***

(b) Bank loans	Large firms					SMEs				
	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Entire period	0.040	0.035	0.005	0.075	0.060	0.049	0.042	0.006	0.091	0.074
Expansions	0.039	0.037	0.002	0.076	0.062	0.048	0.043	0.005	0.091	0.073
Recessions	0.041	0.031	0.009	0.072	0.056	0.050	0.041	0.009	0.091	0.074
H0: Expansions = Recessions		***	***	**	***		**	*		
Not Lost Decade	0.043	0.035	0.008	0.078	0.061	0.054	0.045	0.009	0.099	0.079
Lost Decade	0.033	0.034	-0.001	0.067	0.056	0.038	0.037	0.001	0.075	0.062
H0: Lost Decade = Not-Lost Decade	***		***	***	***	***	***	***	***	***

Table 2: Correlation between credit reallocation measures and aggregate economic conditions

This table presents correlation coefficients between the reallocation measures for interest-bearing debt and lagged and leading aggregate economic conditions. For aggregate economic conditions, real GDP or the DI of business conditions is employed. For real GDP and the credit reallocation measures, the HP filter is employed to extract the cyclical components that we use for the calculation. More details of the filtering are provided in Section 4.1. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Large firms

	GDP(t-4)	GDP(t-3)	GDP(t-2)	GDP(t-1)	GDP(t)	GDP(t+1)	GDP(t+2)	GDP(t+3)	GDP(t+4)
POS	0.510	0.442	0.349	0.183	-0.010	-0.067	0.019	-0.049	0.000
	***	***	***	**					
NEG	-0.198	-0.155	-0.190	-0.130	0.006	0.071	0.179	0.264	0.295
	**	*	**				**	***	***
SUM	0.305	0.279	0.200	0.086	0.009	-0.065	0.121	0.081	0.155
	***	***	**						*
EXC	0.253	0.136	0.052	-0.014	-0.067	0.027	0.070	0.166	0.187
	***							*	**

	DI(t-4)	DI(t-3)	DI(t-2)	DI(t-1)	DI(t)	DI(t+1)	DI(t+2)	DI(t+3)	DI(t+4)
POS	0.408	0.362	0.280	0.164	0.083	0.017	0.011	0.014	0.011
	***	***	***	*					
NEG	0.048	0.083	0.134	0.178	0.211	0.231	0.235	0.228	0.204
				**	**	***	***	***	**
SUM	0.370	0.343	0.301	0.236	0.193	0.137	0.136	0.142	0.130
	***	***	***	***	**			*	
EXC	0.257	0.256	0.219	0.179	0.134	0.126	0.121	0.133	0.118
	***	***	***	**					

SMEs

	GDP(t-4)	GDP(t-3)	GDP(t-2)	GDP(t-1)	GDP(t)	GDP(t+1)	GDP(t+2)	GDP(t+3)	GDP(t+4)
POS	0.166	0.221	0.237	0.264	0.228	0.208	0.195	0.175	0.210
	*	***	***	***	***	**	**	**	**
NEG	-0.049	-0.039	-0.043	0.031	0.064	0.117	0.150	0.166	0.205
							*	*	**
SUM	0.058	0.095	0.104	0.174	0.178	0.190	0.212	0.222	0.255
				**	**	**	**	***	***
EXC	0.108	0.133	0.084	0.121	0.114	0.141	0.114	0.081	0.145
						*			*

	DI(t-4)	DI(t-3)	DI(t-2)	DI(t-1)	DI(t)	DI(t+1)	DI(t+2)	DI(t+3)	DI(t+4)
POS	0.319	0.370	0.371	0.334	0.254	0.205	0.153	0.120	0.091
	***	***	***	***	***	**	*		
NEG	0.110	0.110	0.129	0.145	0.131	0.119	0.118	0.112	0.103
				*					
SUM	0.253	0.283	0.297	0.280	0.231	0.197	0.168	0.143	0.119
	***	***	***	***	***	**	**	*	
EXC	0.180	0.207	0.211	0.212	0.154	0.119	0.091	0.074	0.069
	**	**	**	**	*				

Table 3: Summary statistics for variables used in the estimations

This table reports summary statistics for the dataset used for the estimations in Section 6. Definitions of the variables are provided in Section 4.2.

	N	mean	sd	min	p10	p25	p50	p75	p90	max
Debt_growth	1349175	-0.007	0.363	-2.000	-0.169	-0.051	0.000	0.033	0.170	2.000
BankLoan_growth	1349175	-0.010	0.376	-2.000	-0.171	-0.049	0.000	0.023	0.165	2.000
$\ln TFP_{t-1}$	1349175	-0.146	0.412	-3.740	-0.628	-0.266	-0.066	0.075	0.205	1.816
GDP_hp	1349175	0.000	0.015	-0.060	-0.017	-0.009	0.001	0.009	0.018	0.036
DI	1349175	-10.222	20.094	-49	-36	-24	-11	1	12	41
$\ln Assets_{t-1}$	1349175	8.578	2.036	2.398	5.730	7.220	8.760	9.979	11.051	13.823
$Sales\_growth_{t-1}$	1349175	0.109	0.611	-0.933	-0.267	-0.095	0.015	0.146	0.439	8.725
ROA_{t-1}	1349175	0.009	0.035	-0.316	-0.020	-0.002	0.008	0.021	0.040	0.246
$Capital\_ratio_{t-1}$	1349175	0.307	0.292	-1.427	0.027	0.123	0.280	0.493	0.699	1.000
Industry dummies										
Agriculture, forestry, and fishery	1349175	0.010								
Mining and quarrying of sand and gravel	1349175	0.007								
Construction	1349175	0.079								
Food processing	1349175	0.040								
Textiles and clothing	1349175	0.020								
Wood and wood products	1349175	0.007								
Pulp and paper	1349175	0.012								
Printing and allied industries	1349175	0.011								
Chemicals	1349175	0.050								
Petroleum and coal products	1349175	0.007								
Ceramic products	1349175	0.021								
Iron and steel	1349175	0.017								
Non-ferrous metal	1349175	0.016								
Metal products	1349175	0.024								
General and precision machinery	1349175	0.053								
Electrical and IT machinery	1349175	0.055								
Automobiles and parts	1349175	0.027								
Other transportation machinery	1349175	0.007								
Other manufacturing	1349175	0.035								
Wholesale	1349175	0.134								
Retail	1349175	0.085								
Real estate	1349175	0.053								
Information and telecommunication	1349175	0.033								
Land, water, and other transportation	1349175	0.066								
Electricity, gas, heat supply, water	1349175	0.012								
Other services	1349175	0.119								

Table 4: Baseline estimation

This table reports the estimation results for the growth of interest-bearing debt. Definitions of variables are provided in Section 4.2. Robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Dependent variable: Debt_growth Estimation method: OLS	Entire period				Before Lost Decade		Lost Decade		After Lost Decade	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnTFP$_{t-1}$	0.00199**	0.00150	0.00202**	0.00471***	0.0155***	0.0160***	-0.00323**	-0.00340**	0.00521***	0.00519***
	(0.000929)	(0.000930)	(0.000930)	(0.00110)	(0.00266)	(0.00265)	(0.00155)	(0.00155)	(0.00142)	(0.00142)
GDP_hp	0.116***		0.121***		0.208***		0.251***		-0.0119	
	(0.0215)		(0.0244)		(0.0502)		(0.0386)		(0.0299)	
DI		0.000279***		0.000313***		6.33e-05**		0.000297***		4.55e-06
		(1.56e-05)		(1.80e-05)		(2.83e-05)		(2.81e-05)		(3.87e-05)
lnTFP$_{t-1}$*GDP_hp			0.0327							
			(0.0475)							
lnTFP$_{t-1}$*DI				0.000239***						
				(3.93e-05)						
lnAssets$_{t-1}$	-0.00108***	-0.00101***	-0.00108***	-0.00104***	-0.000424	-0.000523	-0.00113***	-0.00113***	-0.000761***	-0.000760***
	(0.000157)	(0.000157)	(0.000157)	(0.000157)	(0.000319)	(0.000319)	(0.000258)	(0.000258)	(0.000257)	(0.000257)
Sales_growth$_{t-1}$	0.00339***	0.00345***	0.00339***	0.00343***	0.00167	0.00163	0.00550***	0.00552***	0.00297***	0.00296***
	(0.000629)	(0.000629)	(0.000629)	(0.000629)	(0.00124)	(0.00124)	(0.000944)	(0.000944)	(0.00111)	(0.00111)
ROA$_{t-1}$	-0.398***	-0.407***	-0.398***	-0.409***	-0.365***	-0.365***	-0.402***	-0.408***	-0.514***	-0.514***
	(0.0125)	(0.0125)	(0.0125)	(0.0126)	(0.0257)	(0.0257)	(0.0210)	(0.0211)	(0.0202)	(0.0202)
Capital_ratio$_{t-1}$	0.00578***	0.00642***	0.00578***	0.00653***	0.0331***	0.0330***	0.00425**	0.00472**	0.0151***	0.0151***
	(0.00119)	(0.00119)	(0.00119)	(0.00119)	(0.00317)	(0.00318)	(0.00201)	(0.00201)	(0.00178)	(0.00178)
Constant	-0.00320	-0.00141	-0.00317	-0.000717	0.00630	0.00694	-0.00713*	-0.00130	-0.0166***	-0.0166***
	(0.00268)	(0.00268)	(0.00268)	(0.00269)	(0.00515)	(0.00515)	(0.00408)	(0.00411)	(0.00479)	(0.00480)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,349,175	1,349,175	1,349,175	1,349,175	347,179	347,179	484,597	484,597	517,399	517,399
R-squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002

Table 5: Estimation for bank loans

This table reports the estimation results for the growth of loans from financial institutions. Definitions of variables are provided in Section 4.2. Robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Dependent variable: BankLoan_growth										
Estimation method: OLS										
	Entire period				Before Lost Decade		Lost Decade		After Lost Decade	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$lnTFP_{t-1}$	0.00363***	0.00324***	0.00365***	0.00511***	0.0159***	0.0164***	-0.00144	-0.00159	0.00629***	0.00631***
	(0.000916)	(0.000917)	(0.000917)	(0.00109)	(0.00275)	(0.00275)	(0.00158)	(0.00158)	(0.00133)	(0.00133)
GDP_hp	0.0941***		0.0976***		0.255***		0.208***		-0.0450	
	(0.0216)		(0.0240)		(0.0558)		(0.0423)		(0.0282)	
DI		0.000223***		0.000242***		3.21e-05		0.000253***		-4.92e-05
		(1.69e-05)		(1.92e-05)		(3.12e-05)		(3.10e-05)		(3.71e-05)
$lnTFP_{t-1}$*GDP_hp			0.0255							
			(0.0469)							
$lnTFP_{t-1}$*DI				0.000139***						
				(4.12e-05)						
$lnAssets_{t-1}$	-0.00151***	-0.00146***	-0.00151***	-0.00147***	-0.00154***	-0.00162***	-0.000685**	-0.000686**	-0.00173***	-0.00174***
	(0.000167)	(0.000168)	(0.000167)	(0.000168)	(0.000364)	(0.000362)	(0.000284)	(0.000284)	(0.000254)	(0.000254)
$Sales\_growth_{t-1}$	0.00383***	0.00388***	0.00383***	0.00387***	0.00314**	0.00312**	0.00504***	0.00506***	0.00362***	0.00361***
	(0.000633)	(0.000633)	(0.000633)	(0.000633)	(0.00129)	(0.00129)	(0.000974)	(0.000973)	(0.00107)	(0.00107)
ROA_{t-1}	-0.260***	-0.267***	-0.260***	-0.268***	-0.303***	-0.302***	-0.298***	-0.303***	-0.291***	-0.291***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0263)	(0.0263)	(0.0205)	(0.0206)	(0.0180)	(0.0180)
$Capital\_ratio_{t-1}$	0.0120***	0.0125***	0.0120***	0.0126***	0.0324***	0.0324***	0.0126***	0.0130***	0.0236***	0.0236***
	(0.00122)	(0.00122)	(0.00122)	(0.00122)	(0.00345)	(0.00346)	(0.00215)	(0.00215)	(0.00172)	(0.00172)
Constant	-0.00942***	-0.00800***	-0.00940***	-0.00759***	0.00354	0.00430	-0.0209***	-0.0160***	-0.0167***	-0.0172***
	(0.00289)	(0.00289)	(0.00289)	(0.00290)	(0.00582)	(0.00582)	(0.00473)	(0.00475)	(0.00475)	(0.00476)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,349,179	1,349,179	1,349,179	1,349,179	347,181	347,181	484,598	484,598	517,400	517,400
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Table 6: Estimation including/excluding exiting firms

This table reports the estimation results for the growth of debt using the dataset that includes or excludes exiting firms. Years included in the dataset span between 2000 and 2013. The table also provides a comparison between surviving and exiting firms in the dataset. Definitions of variables are provided in Section 4.2. Robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Dependent variable: Debt_growth Estimation method: OLS									Comparison of means between surviving and exiting firms		
	Post-lost decade										
	Including exiting firms				Excluding exiting firms				Surviving firms	Exiting firms	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\ln TFP_{t-1}$	0.00454**	0.00440**	0.00448**	0.00409*	0.00369*	0.00364*	0.00365*	0.00429*	-0.074	-0.086	0.011
	(0.00208)	(0.00208)	(0.00208)	(0.00245)	(0.00196)	(0.00196)	(0.00196)	(0.00232)			
GDP_hp	0.0282		0.0251		0.0244		0.0227		0.000	0.000	0.000
	(0.0384)		(0.0403)		(0.0371)		(0.0391)				
DI		9.83e-05**		9.61e-05*		4.26e-05		4.73e-05	-10.100	-11.903	1.802 ***
		(4.92e-05)		(5.23e-05)		(4.72e-05)		(5.06e-05)			
$\ln TFP_{t-1}$*GDP_hp			-0.0454				-0.0250				
			(0.0843)				(0.0797)				
$\ln TFP_{t-1}$*DI				-2.64e-05				5.61e-05			
				(0.000109)				(0.000101)			
$\ln Assets_{t-1}$	0.00221***	0.00223***	0.00222***	0.00223***	0.000588	0.000595	0.000590	0.000591	9.235	8.294	0.941 ***
	(0.000414)	(0.000414)	(0.000414)	(0.000414)	(0.000398)	(0.000398)	(0.000398)	(0.000398)			
$Sales\_growth_{t-1}$	0.00761***	0.00762***	0.00762***	0.00762***	0.00749***	0.00749***	0.00749***	0.00750***	0.087	0.068	0.019
	(0.00164)	(0.00164)	(0.00164)	(0.00164)	(0.00161)	(0.00161)	(0.00161)	(0.00161)			
ROA_{t-1}	-0.603***	-0.605***	-0.603***	-0.605***	-0.649***	-0.650***	-0.649***	-0.650***	0.009	0.001	0.008 ***
	(0.0330)	(0.0330)	(0.0330)	(0.0331)	(0.0317)	(0.0317)	(0.0317)	(0.0317)			
$Capital\_ratio_{t-1}$	0.0419***	0.0419***	0.0419***	0.0419***	0.0222***	0.0222***	0.0222***	0.0222***	0.382	0.200	0.182 ***
	(0.00273)	(0.00273)	(0.00273)	(0.00273)	(0.00254)	(0.00254)	(0.00254)	(0.00254)			
Constant	-0.0489***	-0.0481***	-0.0489***	-0.0481***	-0.0257***	-0.0253***	-0.0257***	-0.0252***			
	(0.00912)	(0.00913)	(0.00913)	(0.00914)	(0.00866)	(0.00867)	(0.00866)	(0.00868)			
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes			
Observations	360,121	360,121	360,121	360,121	358,641	358,641	358,641	358,641	358,641	1,480	
R-squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002			

Figure 1: Developments in the extent of credit reallocation

This figure depicts developments in the credit reallocation measures over the entire observation period. We use interest-bearing debt as the credit variable. Gray shaded areas represent short-term recessionary periods. The Lost Decade is from FY1990 Q4 to FY2001 Q4, which is from the start of the third short-term recession to the end of the fifth recession in each chart. We use X-12-ARIMA to adjust for seasonality in our credit reallocation measures.

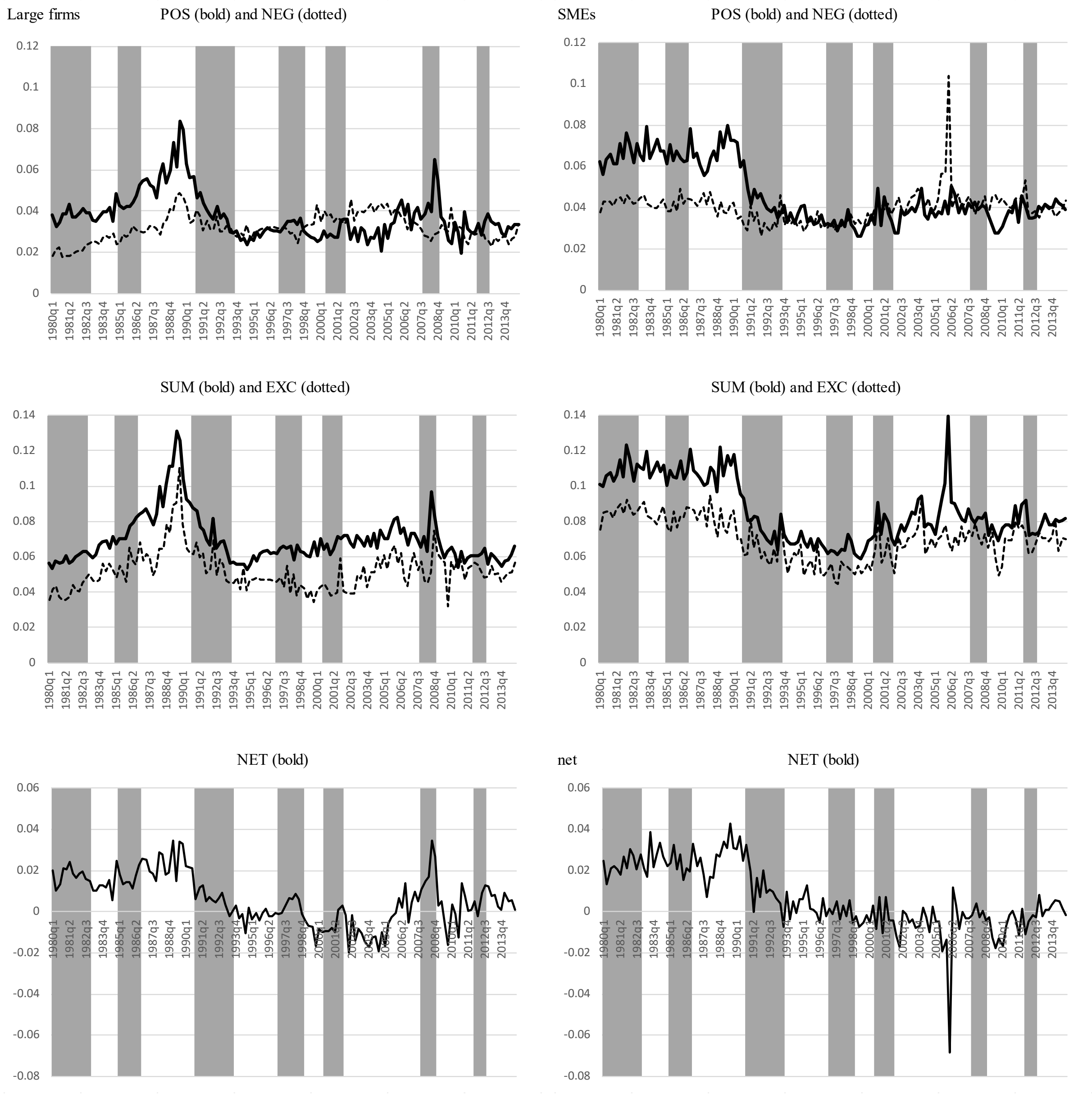
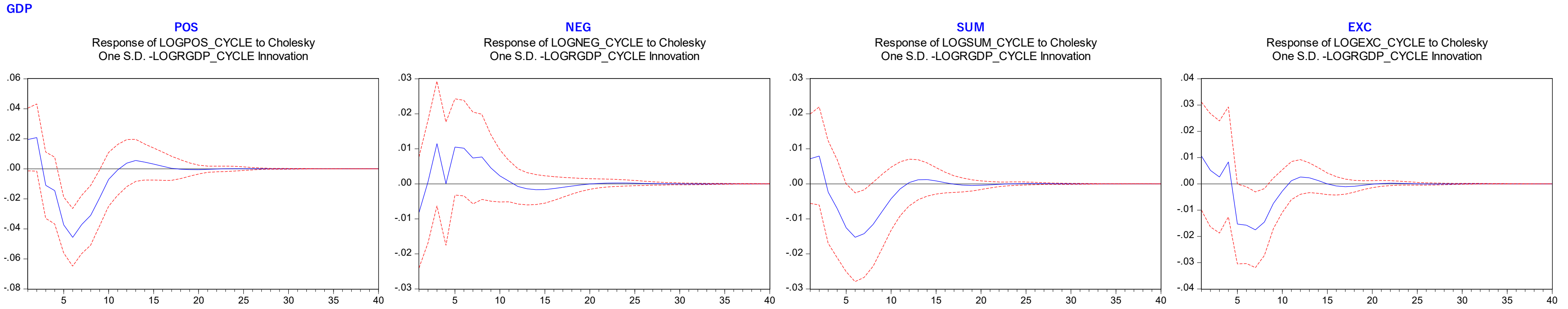


Figure 2: Impulse responses to a one standard deviation negative aggregate shock: Large firms
This figure shows the impulse responses of the reallocation measures for interest-bearing debt to a one standard deviation negative aggregate shock. We model aggregate shocks as (a) a shock to real GDP and (b) a shock to the DI of business conditions. The blue line in each chart represents the response of the credit reallocation measure, while the red dotted lines show the 95 percent confidence band. We calculate the series used for VAR following the procedure detailed in Section 4.1.

(a) Real GDP



(b) DI of business conditions

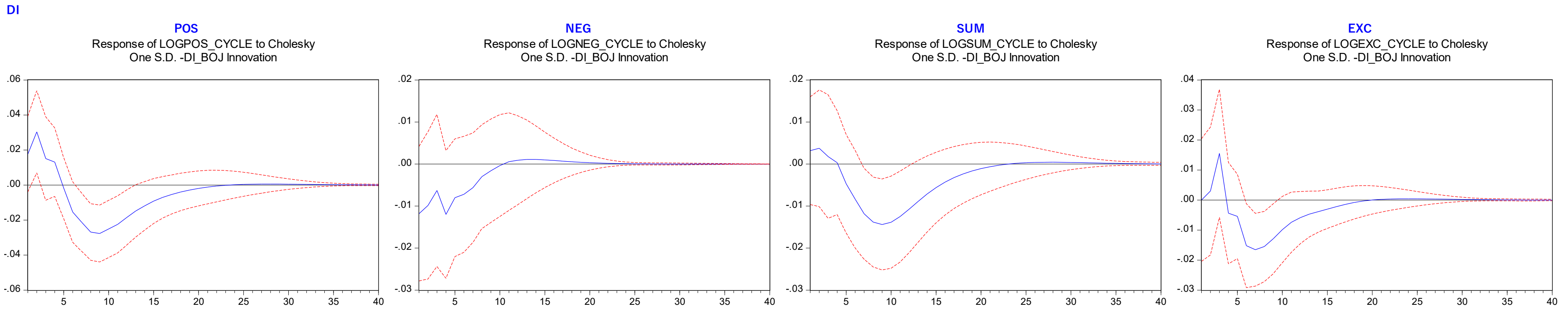
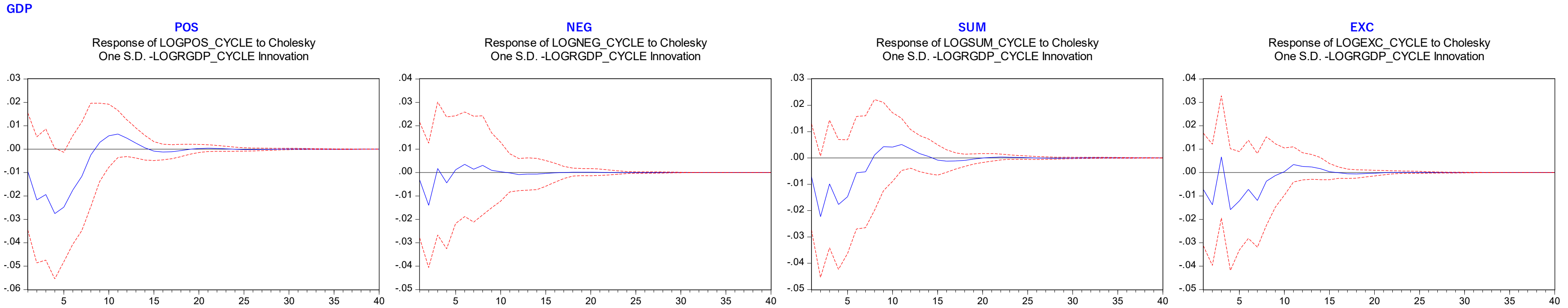


Figure 3: Impulse responses to a one standard deviation negative aggregate shock: SMEs

This figure measures the impulse responses of the reallocation measures for interest-bearing debt to a one standard deviation negative aggregate shock. We model aggregate shocks as (a) a shock to real GDP and (b) a shock to the DI of business conditions. The blue line in each chart represents the response of the credit reallocation measure, while the red dotted lines show the 95 percent confidence band. We calculate the series used for VAR following the procedure detailed in Section 4.1.

(a) Real GDP



(b) DI of business conditions

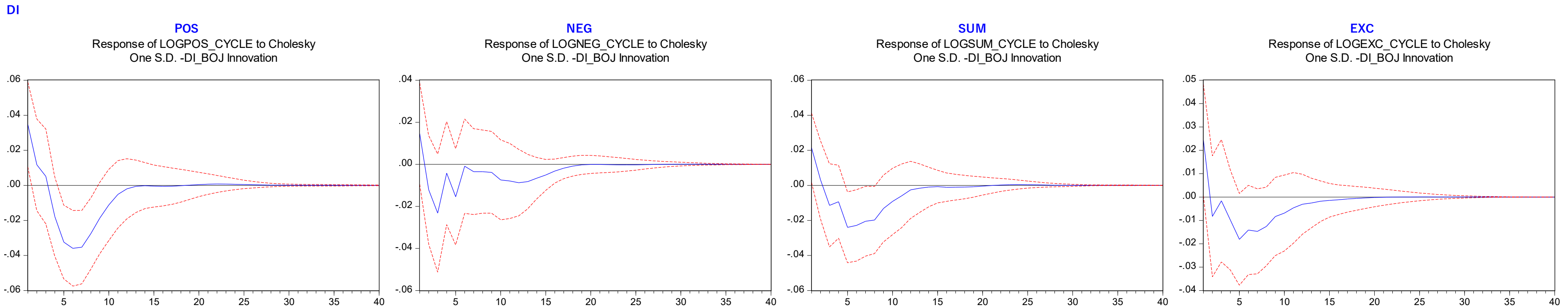


Figure 4: Development in the dispersion of TFP
This figure plots the standard deviation of the difference between the log of firms' TFP and the average TFP level in the year and industry the firm belongs to.

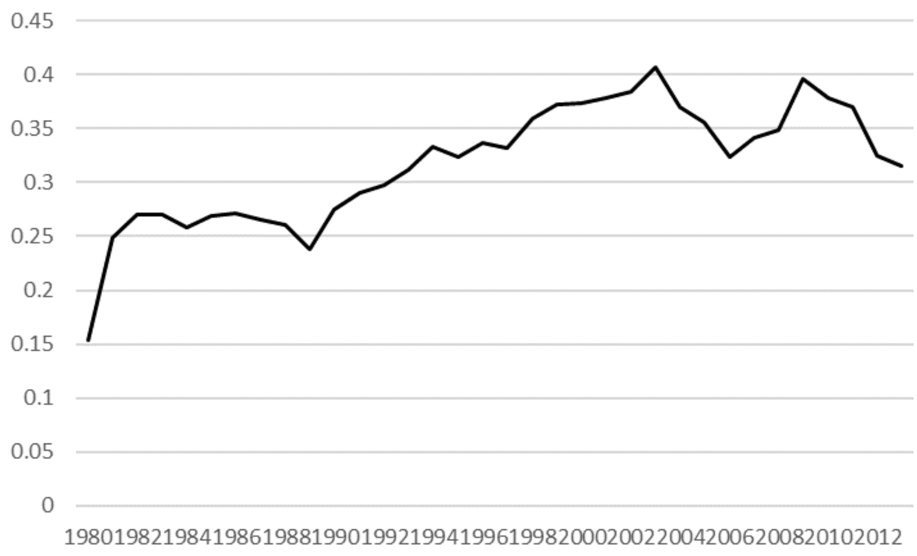
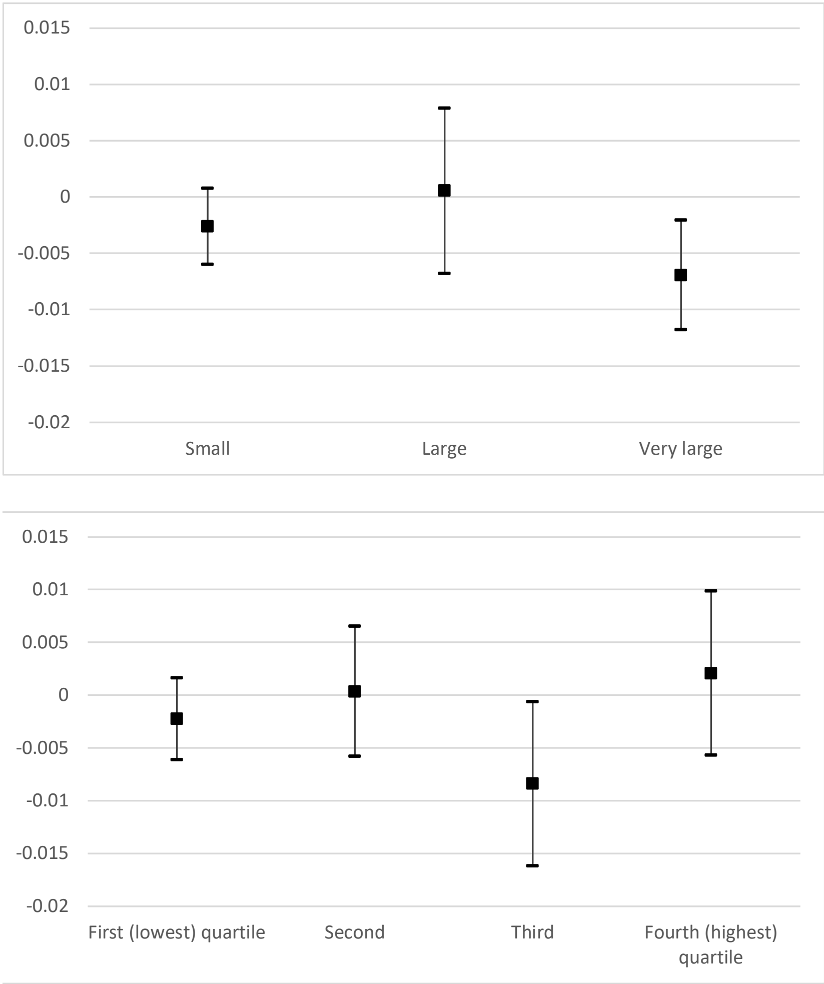


Figure 5: Coefficients on lnTFP for different subsamples in the Lost Decade

This figure plots the coefficients on lnTFP using specification (8) for various subsamples. Focusing on the Lost Decade, we construct subsamples based on firms' size or capital ratio and conduct estimations. The left panels show the results using debt growth as the dependent variable, while the right panels show the results using bank loans as the dependent variable. The square dots represent the coefficient estimates, while the vertical lines represent the 95% confidence intervals.

(a) Debt growth as dependent variable



(b) Bank loan growth as dependent variable

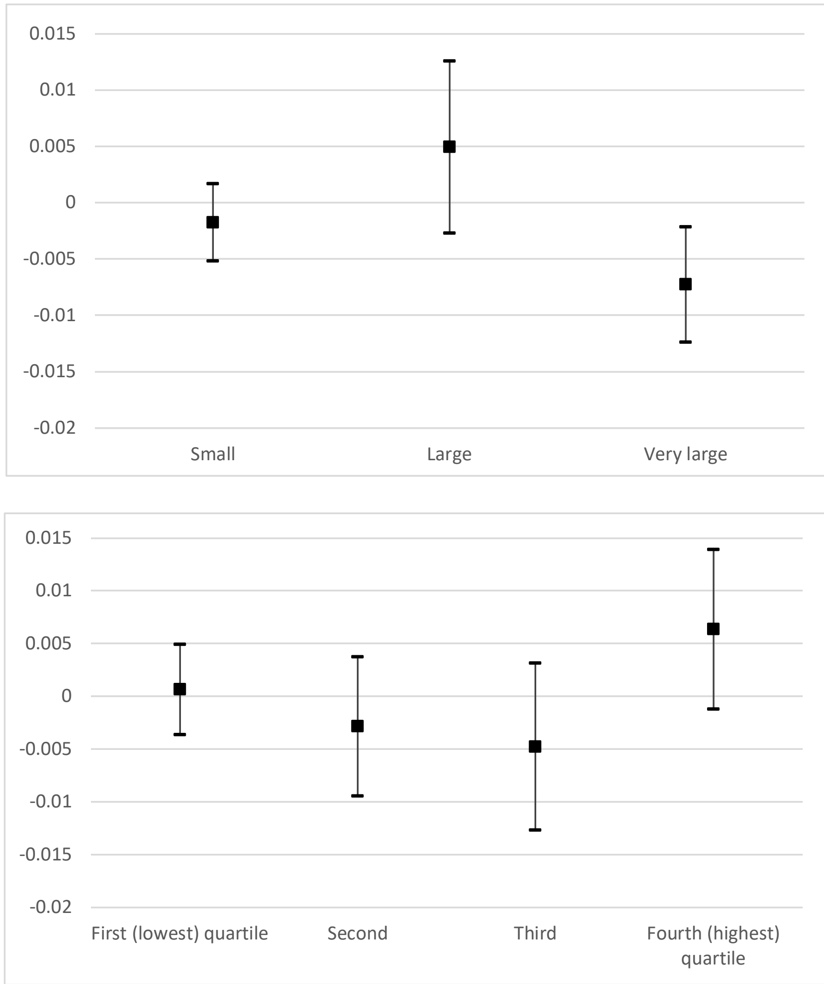
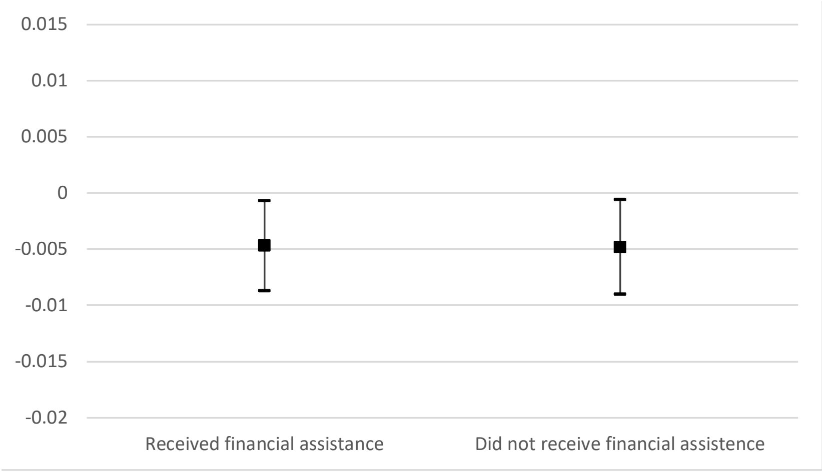


Figure 6: Coefficients on lnTFP for firms that received and did not receive financial assistance in the Lost Decade

This figure plots the coefficients on lnTFP using specification (8) for various subsamples. Focusing on the Lost Decade, we construct subsamples based on whether firms received financial assistance and conduct estimations. The left panel shows the results using debt growth as the dependent variable, while the right panel shows the results using bank loans as the dependent variable. The square dots represent the coefficient estimates, while the vertical lines represent the 95% confidence intervals.

(a) Debt growth as the dependent variable



(b) Bank loan growth as the dependent variable

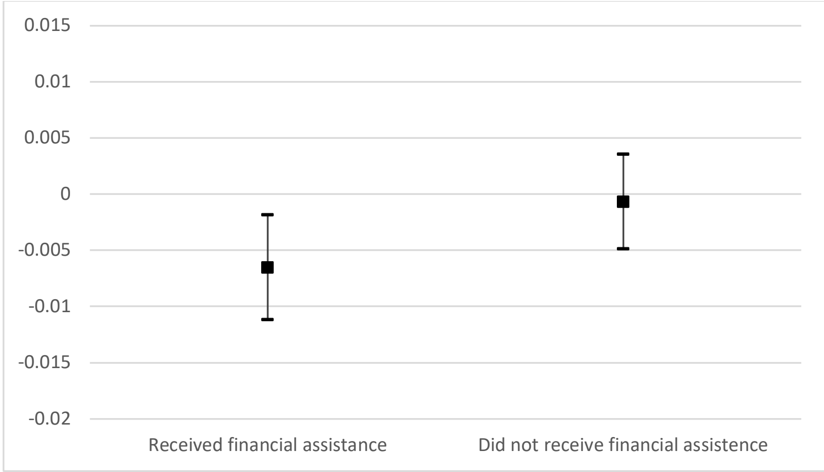
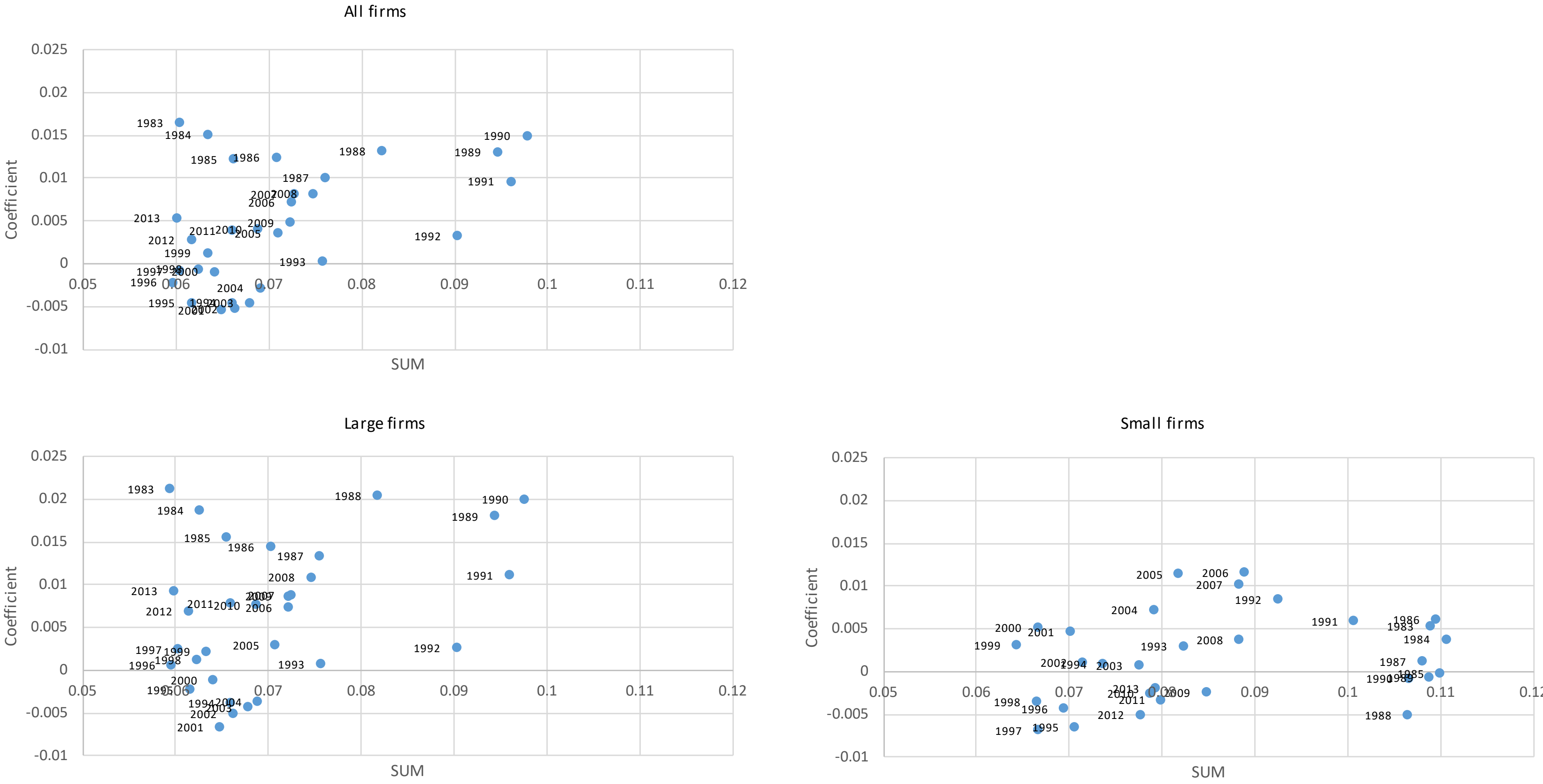


Figure 7: The extent of credit reallocation and coefficients on lnTFP

This figure plots the average extent of aggregate credit reallocation (SUM) along the horizontal axis for a four-year period and the size of the coefficients on lnTFP in rolling regressions for a period of four years along the vertical axis. For the rolling regressions, we employ specification (8). The labels attached to the dots in the figure represent the end year of the sample used for each estimation and calculation of credit reallocation. Note that not all the coefficients in the estimations are statistically different from zero.



Online Appendix

A. Firm-level data from the Quarterly Financial Statements Statistics of Corporations by Industry

The Quarterly Financial Statements Statistics of Corporations by Industry (QFSSC) are a survey of business corporations whose headquarters are located in Japan. The QFSSC started in the fourth quarter of fiscal 1949, and firm-level data in electronic form are available to researchers (after a time-consuming application process) for the period from the first quarter of fiscal 1980.

The QFSSC contain information on individual corporations' balance sheets, employment, industry, geographic location, transactions in fixed assets, etc. They cover all manufacturing and non-manufacturing industries, although we exclude finance and insurance from the analysis. The QFSSC consist of two parts: a part that targets all large corporations, and a part that consists of a sample of smaller firms.

There was a substantial change in fiscal 2009 in the way firms were chosen for the survey. Up to the fourth quarter of fiscal 2008, the first part of the survey targeted all corporations with paid-in capital of 600 million yen or more, and observations consisted of all such corporations that responded to the questionnaire, while the second part consisted of a sample of smaller firms, which were subdivided into those with paid-in capital ranging from 100 to 600 million yen and those with paid-in capital of less than 100 million yen. In the second part, sampling was conducted in a manner such that among firms in the 100 to 600 million yen bracket larger firms were more likely to be chosen, while among firms with paid-in capital of less than 100 millions firms were chosen randomly regardless of their capital size. All smaller firms with paid-in capital of less than 600 million yen that were surveyed received a questionnaire for four quarters from the first to the fourth quarter of the fiscal year, while all larger corporations always received a survey questionnaire.

Since the first quarter of fiscal 2009, the first part targets all corporations with paid-in capital of 500 million yen (instead of 600 million yen) or more. On the other hand, the second part is no longer subdivided. Instead, firms are randomly chosen from the pool of firms with paid-in capital of less than 500 million yen. All firms with less than 500 million yen of paid-in capital that are surveyed receive a questionnaire for eight quarters (two years), with half of the firms replaced in the first quarter of each fiscal year. As before, all larger corporations continue to always receive the survey questionnaire.

B. Construction of the data set that incorporates firm entry and exit

In this appendix, we explain the procedure we use to identify the timing of the entry and exit of firms in the QFSSC. The QFSSC do not have information on firm age or the year that a firm exited from the market. To obtain this information, we employ another data source provided by Teikoku Databank (TDB), one of Japan's largest private credit research companies. TDB has a comprehensive database called COSMOS2 that contains information on more than four million firms in Japan.[23] From the database, information on corporations with 40 employees or more from 1999 and onward is available for researchers.

Since the QFSSC and the dataset extracted from COSMOS2 do not use the same identification numbers for firms, we use firms' name, reporting year, the amount of paid-in capital, and the prefecture in which a firm is located to match observations in the two datasets. The total number of observations that we can match for the period from 1999 and 2014 is 695,599.

Using this dataset, we identify the year a firm first shows up and the year it is last recorded in the data and regard these years as the firm's years of entry and exit. If this entry year in COSMOS2 is the same as the year a firm first shows up in the QFSSC, we identify this

[23] The TDB website states that the company holds information on about 4.2 million firms (see https://www.tdb.co.jp/info/topics/k170501.html, in Japanese, accessed March 21, 2021). Government statistics indicate that currently there are 1.5 million corporations and 2.3 million proprietorships, totaling 3.8 million firms, suggesting that the TDB database covers almost the entire universe of Japanese firms.

as the firm's entry year. Similarly, we define a firm's exit year when the firm's exit year in COSMOS2 matches the year the firm responded to the QFSSC survey for the last time.

In the analysis, we use this dataset to examine the impact of firm entry and exit on the extent of credit reallocation. We also test whether including these entering and exiting firms changes the estimation results on the extent to which credit reallocation is efficiency-enhancing.

C. Calculation of TFP

Another important variable we construct is the variable for firms' productivity. Firm-level TFP can be calculated using one of two different methods: subtracting the cost share of each input from output, or estimating a production function and using the parameters obtained from the estimation. In order to calculate TFP values for as many observations as possible and use them for later analysis, we employ the former approach, which is also used by Foster, Grim, and Haltiwanger (2016), one of a limited number of studies on the relationship between resource reallocation and TFP. Note, however, that this method requires the possibly unrealistic assumption of perfect competition.

Among a variety of approaches based on the latter method, researchers most frequently employ the control function approach, which was originally proposed by Olley and Pakes (1996) and developed by Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015), among others. The reason we do not employ this approach is that it requires lagged values and we would need to drop a large number of observations for SMEs, since for many of them lagged values are not available. Following Good, Nadiri, and Sickles (1997), Aw, Chen, and Roberts (2001) and Fukao and Kwon (2006), we define the TFP level of firm f at time t in a certain industry relative to the TFP level of a representative firm in the base year 0 in that industry based on the following equation:

$$lnTFP_{ft} = \left(lnY_{ft} - \overline{lnY_t}\right) + \sum_{s=1}^{t}\left(\overline{lnY_s} - \overline{lnY_{s-1}}\right) - \left[\sum_{i=1}^{n}\frac{1}{2}\left(S_{ift} + \overline{S_{it}}\right)\left(lnX_{ift} - \overline{lnX_{it}}\right) + \sum_{s=1}^{t}\sum_{i=1}^{n}\frac{1}{2}\left(\overline{S_{is}} - \overline{S_{is-1}}\right)\left(\overline{lnX_{is}} - \overline{lnX_{is-1}}\right)\right] \quad \text{(C.1)}$$

where Y_{ft}, S_{ift}, and X_{ift} denote the gross output (sales) of firm *f* at time *t*, the cost share of factor *i* for firm *f* at time *t*, and firm *f*'s input of factor *i* at time *t*, respectively. Variables with an upper bar denote the industry average of that variable. As input factors, we include capital, labor, and intermediate inputs. The details of the construction of the output and input factor variables are as follows.

Output

We use each firm's total sales for nominal gross output. We construct the output deflator for a particular year by dividing the industry-level nominal gross output by the real gross output obtained from the JIP database. We calculate the deflator annually rather than quarterly, because the JIP database provides value-added statistics only at an annual frequency.

Labor

For L_{it}, we calculate the total hours worked based on the following formula:

$L_{it} = Number\ \ of\ \ Employees_{it} * Yearly\ \ Hours\ \ \ Worked_{st}$.

We obtain the firm-level number of employees from the QFSSC. We also calculate industry-level yearly hours worked per person from the hours worked and the number of employees in the JIP database.

Capital

We calculate real capital (non-land tangible assets) K_{it} at market prices from the information on the nominal book value of a firm's capital in the QFSSC, KN_{it}. We first calculate industry-level series of non-land tangible assets in terms of their market value, K_{sy}, for a particular year y, using the following formula:

$$K_{s0} = \frac{KN_{s0}}{PINVEST_{s0}}$$

$$K_{sy} = \left(1 - \delta_{sy}\right)K_{sy-1} + \frac{INVEST_{sy}}{PINVEST_{sy}}, \text{ t=1,…, Y,}$$

where KN_{sy} is the industry-level nominal amount of non-land tangible assets outstanding measured at the end of y, $PINVEST_{sy}$ is the industry-level investment deflator, $INVEST_{sy}$ is the nominal amount of investment in non-land tangible assets, and δ_{sy} is the industry-level depreciation rate. We set the year 1975 as the starting year, i.e., y=0. All information for the above calculations is obtained from the JIP database and the *Annual Financial Statements Statistics of Corporations by Industry*. The *Annual Financial Statements Statistics of Corporations by Industry* (AFSSC) are annual statistics on firms' financial statements, which, like the QFSSC, are compiled by Ministry of Finance. We employ the AFSSC instead of the QFSSC since we construct the variable $Ratio$ at an annual frequency. We obtain the industry-level market-to-book value ratio and the firm-level amount of real non-land tangible assets at market prices using the following formula:

$$Ratio_{sy} = \frac{K_{sy}}{KN_{sy}}$$

$$K_{it} = Ratio_{sy} * KN_{it}.$$

Intermediate inputs

We calculate the real firm-level input of intermediate goods, M_{it}, using the following formula:

$$M_{it} = \frac{Sales\ \ Cost_{it} + Sales\ \ Administrative\ \ Expense_{it} - (Personnel\ \ Cost_{it} + Depreciation_{it})}{PM_{sy}},$$

where PM_{sy} is the industry-level intermediate input deflator in year y calculated from the industry-level nominal intermediate inputs and real intermediate inputs obtained from the JIP database.

We also need to specify the industries that we use to calculate firms' TFP based on equation

(C.1). In principle, we use the industry classifications employed in the QFSSC. However, we combine some of the categories to have consistent industry classifications before and after the revision of classifications in the QFSSC in 2009. We also do this in order to be able to match the classifications with those used in the JIP database. The following is a list of industry classifications (which roughly follow the Japan Standard Industrial Classification) used for the analysis.

Industry classification used for the analysis

Industry code	Name of industry
1	Agriculture, forestry, and fishery
10	Mining and quarrying of sand and gravel
15	Construction
18	Food processing
20	Textiles and clothing
22	Wood and wood products
24	Pulp and paper
25	Printing and allied industries
26	Chemicals
27	Petroleum and coal products
30	Ceramic products
31	Iron and steel
32	Non-ferrous metals
33	Metal products
34	General and precision machinery
35	Electrical and IT machinery
36	Automobiles and parts
38	Other transportation machinery
39	Other manufacturing
40	Wholesale
49	Retail
59	Real estate
60	Information and telecommunication
61	Land, water, and other transportation
70	Electricity, gas, heat supply, water
75	Other services

D. Impact of including entering and exiting firms on the extent of credit reallocation

In Section 5.1, we limited the scope of the analysis to firms for which observations at both ends of the interval between time *t-1* and *t* are available. This means that we fail to take account of the impact of firms that newly entered or exited the market, possibly resulting in a downward bias in our reallocation measures. We measure the extent of possible biases in the extent of credit reallocation. We also examine how large these biases are in the extent of reallocation during economic downturns and upturns. In this Appendix we employ the dataset described in Section 3.2 and in Appendix B.

Panel (a) of Appendix Table D-1 shows the mean values of the five credit reallocation measures by firm size for the period 2000–2014 when entering and exiting firms are included and when they are excluded. We employ interest-bearing debt as the debt instrument. Since the absolute growth rate of credit for entering and exiting firms is 2 in most cases, which is the maximum possible value, including these firms in the dataset will likely increase POS, NEG, and SUM.[24] And indeed, in the table, the values of these three measures in the second row are larger than those in the first row. We also find that the difference is substantially larger for SMEs than for large firms, reflecting the fact that most entering and exiting firms are small in size.

Next, we examine changes in the extent of credit reallocation during expansionary and contractionary phases. In each of the two datasets, i.e., the dataset without entrant and exiting firms and the dataset including these firms, we compare the extent of credit reallocation between expansionary and contractionary periods.

In panel (b) we show the results. Regardless of firm size, the signs on the differences between the reallocation measures in expansionary and recessionary periods are the same regardless of whether the dataset includes or excludes entering and exiting firms. The statistical significance of these differences is also similar between the two datasets. To summarize, inclusion of entering and exiting firms in the analysis increases the level of credit reallocation, especially for SMEs. However, doing so does not appear to qualitatively change our results

[24] The growth rate of debt (g_{ft}) for an entering firm f is ($Debt_{ft}$-0)/0.5($Debt_{ft}$+0) = 2 if $Debt_{ft}$>0, and that for an exiting firm f is (0-$Debt_{ft-1}$)/0.5(0+$Debt_{ft-1}$) = -2 if $Debt_{ft-1}$>0.

regarding the extent of credit reallocation during an economic downturn. Thus, ignoring firm entry and exit in our analysis does not appear to substantially bias the results.

Appendix Table D-1: Extent of credit reallocation for interest-bearing debt including/excluding entering and exiting firms

This table reports the extent of credit reallocation for interest-bearing debt and (a) compares each of the reallocation measures when entering and exiting are excluded and when they are included. It also (b) compares the extent of reallocation between expansionary and recessionary periods. Definitions of variables are provided in Section 3.2. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

(a) Results for the observation period from FY2000 to FY2014

Large firms	POS	NEG	NET	SUM	EXC	SMEs	POS	NEG	NET	SUM	EXC
2000Q1-2014Q4 (excl. entry & exit)	0.033	0.034	0.000	0.067	0.051	2000Q1-2014Q4 (excl. entry & exit)	0.038	0.043	-0.005	0.081	0.069
2000Q1-2014Q4 (incl. entry & exit)	0.033	0.035	-0.001	0.068	0.053	2000Q1-2014Q4 (incl. entry & exit)	0.041	0.053	-0.011	0.094	0.073
H0: Excl. = Incl.		***	**	***	***	H0: Excl. = Incl.	***	***	***	***	***

(b) Results when distinguishing between expansions and recessions

Large firms 2001Q1-2014Q4 (excl. entry & exit)	POS	NEG	NET	SUM	EXC	SMEs 2001Q1-2014Q4 (excl. entry & exit)	POS	NEG	NET	SUM	EXC
Expansions	0.032	0.034	-0.002	0.066	0.052	Expansions	0.038	0.044	-0.005	0.082	0.069
Recessions	0.037	0.031	0.006	0.068	0.050	Recessions	0.038	0.041	-0.003	0.079	0.068
Difference	-0.005	0.003	-0.009	-0.002	0.002	Difference	0.000	0.003	-0.003	0.002	0.001
H0: Expansions = Recessions	**	*	***			H0: Expansions = Recessions					

2001Q1-2014Q4 (incl. entry & exit)	POS	NEG	NET	SUM	EXC	2001Q1-2014Q4 (incl. entry & exit)	POS	NEG	NET	SUM	EXC
Expansions	0.032	0.035	-0.003	0.067	0.054	Expansions	0.041	0.054	-0.012	0.095	0.073
Recessions	0.037	0.033	0.004	0.070	0.051	Recessions	0.041	0.048	-0.008	0.089	0.073
Difference	-0.005	0.002	-0.007	-0.002	0.002	Difference	0.001	0.005	-0.004	0.006	0.000
H0: Expansions = Recessions	**		**			H0: Expansions = Recessions					

E. Correlation and vector autoregression results when raw values are employed for the credit reallocation measures and real GDP

This appendix examines what happens when we use the raw values of the credit reallocation measures and real GDP instead of extracting the cyclical component using the Hodrick-Prescott filter. To obtain the raw values of the credit reallocation measures, we follow Dell'Ariccia and Garibaldi (2005) and adjust the original values of the credit reallocation measures by multiplying them by C_{st}. Note, however, that we take the first difference of the raw credit reallocation values and of real GDP, since the null that each of these variables has a unit root is not rejected.

Appendix Table E-1 shows the result for the correlation coefficients. We find that the statistical significance of the correlation coefficients drops substantially from those in Table 2 in the main text. With regard to POS, we find that although only some coefficients are significant, the pattern that emerges is that they are mostly positive both for large firms and SMEs and across different economic conditions. For NEG, the majority of coefficients are still positive regardless of the firm size, although most are insignificant. Possibly as a result of the positive coefficients for POS, the signs of both SUM and EXC are positive in most cases.

Appendix Table E-1: Correlation between credit reallocation measures and aggregate economic conditions

Large firms

	GDP(t-4)	GDP(t-3)	GDP(t-2)	GDP(t-1)	GDP(t)	GDP(t+1)	GDP(t+2)	GDP(t+3)	GDP(t+4)
POS	0.290***	0.077	0.144*	0.074	-0.125	-0.143*	0.231***	-0.109	0.001
NEG	-0.203**	0.144*	-0.056	-0.016	0.146*	0.022	0.104	0.140	0.074
SUM	0.096	0.139	0.133	0.035	0.067	-0.268***	0.381***	-0.073	0.062
EXC	0.255***	0.001	0.024	0.042	-0.118	0.108	-0.009	0.131	0.001

	DI(t-4)	DI(t-3)	DI(t-2)	DI(t-1)	DI(t)	DI(t+1)	DI(t+2)	DI(t+3)	DI(t+4)
POS	0.060	0.102	0.138	0.114	0.098	0.049	0.047	0.058	0.043
NEG	0.007	-0.007	0.006	0.020	0.033	0.048	0.060	0.081	0.095
SUM	0.065	0.087	0.119	0.107	0.116	0.068	0.071	0.096	0.095
EXC	0.030	0.064	0.072	0.082	0.056	0.055	0.045	0.070	0.057

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

SMEs

	GDP(t-4)	GDP(t-3)	GDP(t-2)	GDP(t-1)	GDP(t)	GDP(t+1)	GDP(t+2)	GDP(t+3)	GDP(t+4)
POS	0.073	0.070	0.009	0.101	0.006	0.013	0.037	-0.047	0.046
NEG	-0.032	0.028	-0.082	0.074	-0.013	0.046	0.047	-0.006	0.065
SUM	0.019	0.062	-0.061	0.122	0.013	0.017	0.049	0.000	0.062
EXC	0.074	0.103	-0.087	0.072	-0.023	0.085	0.037	-0.106	0.107

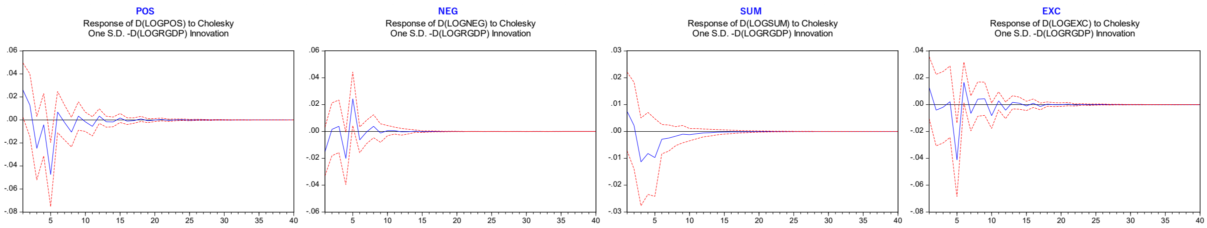
	DI(t-4)	DI(t-3)	DI(t-2)	DI(t-1)	DI(t)	DI(t+1)	DI(t+2)	DI(t+3)	DI(t+4)
POS	-0.054	0.002	0.045	0.093	0.074	0.083	0.072	0.074	0.065
NEG	0.004	-0.009	-0.003	0.029	0.032	0.025	0.033	0.039	0.032
SUM	-0.034	-0.009	0.032	0.073	0.067	0.069	0.069	0.075	0.067
EXC	-0.021	0.006	0.013	0.070	0.060	0.057	0.051	0.045	0.037

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

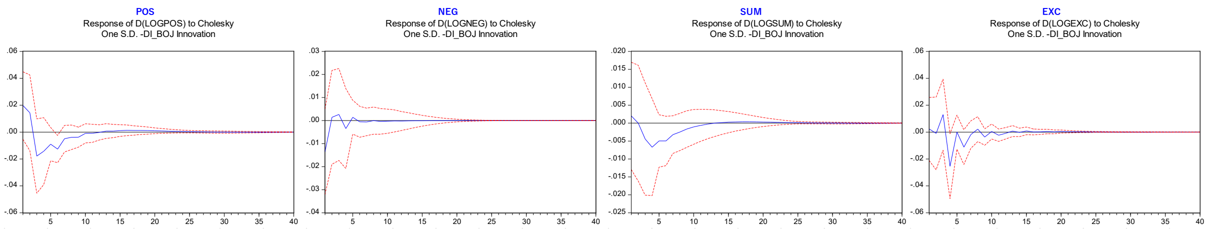
Employing the same set of variables that we use in the calculations for correlation coefficients, we implement VAR. Figures E-1 and E-2 show that the results are weaker than in Figures 2 and 3 in the main text. For large firms, Figure E-1 shows that an adverse shock results in a decrease in EXC but not in SUM both when real GDP and the DI are used, driven by a decrease in POS. For SMEs, Figure E-2 indicates that only an adverse shock to one of the economic indicators (the DI) causes a decline in SUM and EXC after less than five quarters.

Appendix Figure E-1: Impulse responses to a one standard deviation negative aggregate shock: Large firms

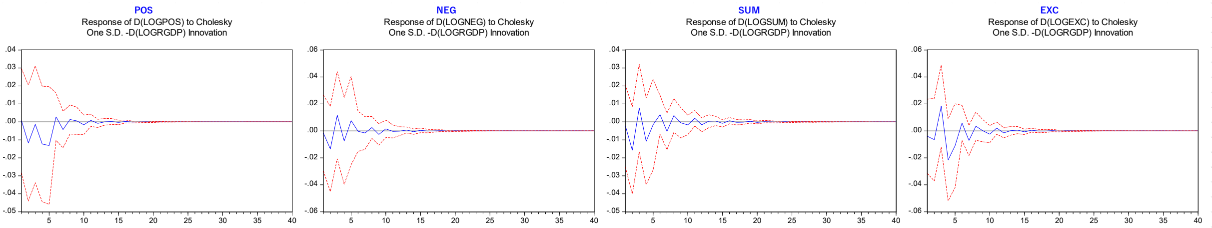
(a) Real GDP



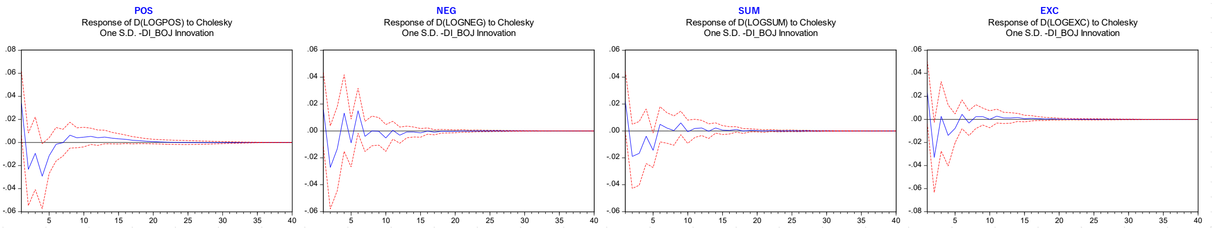
(b) DI of business conditions



Appendix Figure E-2: Impulse responses to a one standard deviation negative aggregate shock: SMEs
(a) Real GDP



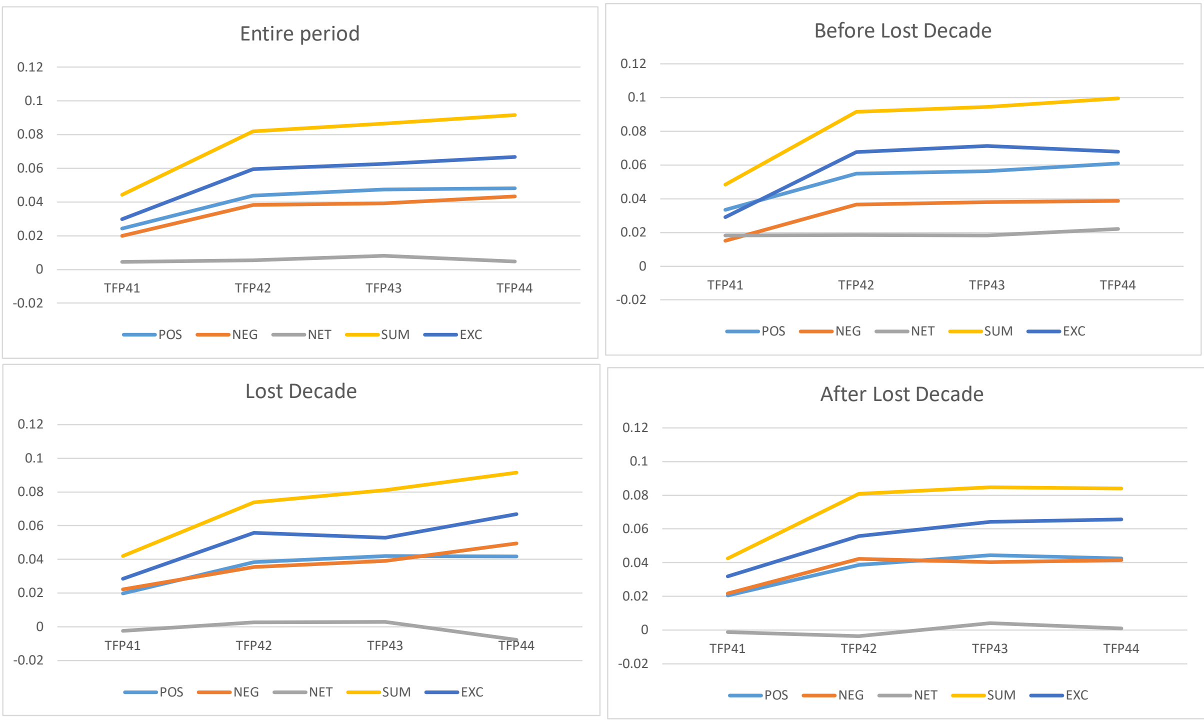
(b) DI of business conditions



F. Relationship between productivity and the extent of credit reallocation

The purpose of the analysis is to relate the extent of credit reallocation to productivity at a somewhat disaggregated level. We divide firms in the dataset in each period into four groups based on their level of TFP in the previous period and measure the extent of reallocation for interest-bearing debt across quartiles in each period. The results in Appendix Figure F-1 indicate the presence of a substantial positive association between productivity and all the reallocation measures except for NET.

Appendix Figure F-1: Extent of credit reallocation by productivity level
This figure presents the extent of reallocation of interest-bearing debt for each quartile group of firms based on their productivity. TFP41 represents firms in the first (lowest) productivity quartile, while TFP 44 represents firms in the fourth (highest) quartile in terms of productivity. The top left panel covers the entire period, while the other three cover the three sub-periods, i.e., before, during, and after the Lost Decade.



G. Identification of firms that received financial assistance

The construction of the variable follows the identification of zombie firms in Caballero, Hoshi, and Kashyap (2008) (hereafter CHK). In order to identify zombie firms using the QFSSC, we limit observations to firms for which financial statement information for all four quarters in a fiscal year is available. We then sum a firm's interest payments and profits over the four quarters in a fiscal year. Moreover, we use a firm's amount of debt outstanding at the end of the fiscal year.

CHK define zombie firms in relation to the hypothetical lower bound for interest payments (R_{it}^*) for the highest quality borrowers, which they define as follows:

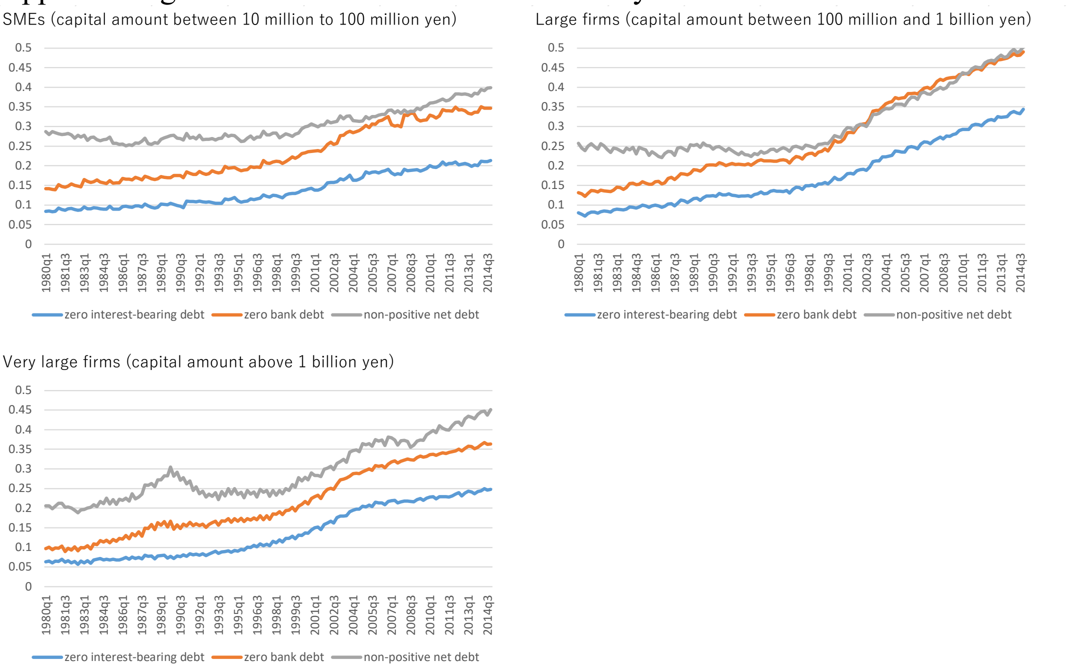
$$R_{it}^* = rs_{t-1}BS_{it-1} + \left(\frac{1}{5}\sum_{j=1}^{5} rl_{t-j}\right) BL_{it-1} + rcb_{\text{min over last 5 years, } t} \times Bonds_{it-1},$$

where BS_{it}, BL_{it}, and $Bonds_{it}$ are short-term bank loans, long-term bank loans, and total bonds outstanding (including convertible bonds) of firm *i* at the end of fiscal year *t*, respectively. The interest rates rs_t and rl_t are the average short-term and long-term prime rates for fiscal year *t*, respectively, and $rcb_{\text{min over last 5 years, } t}$ is the minimum observed rate on any convertible corporate bond issued over the previous five years prior to t. CHK define zombies as firms whose interest payments R_{it} were lower than R_{it}^*. The basic idea is that troubled firms must have received substantial interest relief to be making lower interest payments than healthy firms.

H. Identification of zero leverage firms and negative net worth firms

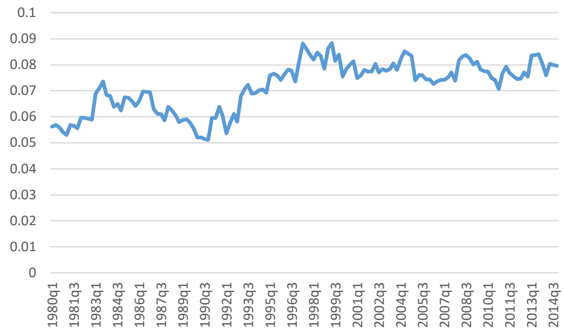
In the appendix, we examine the extent firms that are unlevered as well as firms that are highly levered coexist in the loan market. For this purpose, we present shares of these unlevered and high-levered firms for different firm sizes: very large (whose capital amount exceeds 1 billion yen), large (whose capital amount is between 100 million and 1 billion yen), and SMEs (whose capital amount is between 10 million and 100 million yen). We employ three different definitions for unlevered firms: firms that have no interest-bearing debt amount outstanding, no bank debt amount outstanding, and firms whose cash amount outstanding exceeds the amount of interest-bearing debt. We define highly levered firms as those whose capital ratio is negative. We present results for the unlevered firms in Table H-1 and those for the highly-levered firms in Table H-2.

Appendix Figure H-1: Share of unlevered firms by firm size

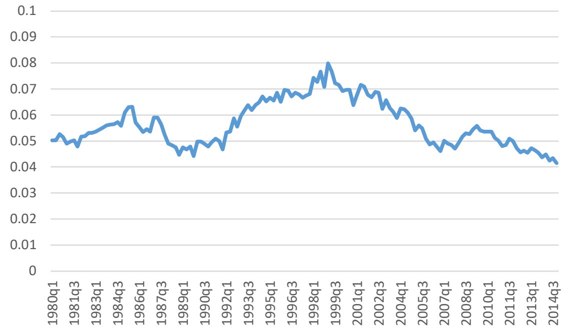


Appendix Figure H-2: Share of negative net worth firms by firm size

SMEs (capital amount between 10 million to 100 million yen)



Large firms (capital amount between 100 million and 1 billion yen)



Very large firms (capital amount above 1 billion yen)