How banks allocate loans in Italy: a long run perspective

De Bonis, Riccardo and Ferri, Giovanni and Forte, Antonio and Silipo, Damiano Bruno

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by

Riccardo De Bonis, Giovanni Ferri, Antonio Forte, and Damiano B. Silipo[1]

ABSTRACT

Finance is a salient driver in promoting growth also by supporting changes in the specialization of production. Thus, it is paramount that finance goes to sunrise productive branches embodying more technology and so higher growth potential. Is it so in reality?

We address this question by investigating the long-run allocation of bank loans in the bank-dependent Italian economy. We reach three main findings. First, banks lent more to the branches where value added was growing more rapidly, while loans went less to riskier sectors with higher bad loans ratios. Second, the allocation of loans was, however, insensitive to the growth of productivity and did not support the higher technology branches. Third, the allocation of loans to the more technology-oriented branches improved since the early 1990s, when credit markets were liberalized.

Overall, in our assessment banks were rather following than leading productive transformations, but managed to avoid large scale misallocation of credit. Hence, we give banks just a pass grade.

JEL codes: G20; G21; O30; O47.

Keywords: Allocation of bank loans; Branch productivity and value added; Long-run perspective; Non performing loans.

1. Introduction

Finance for growth deals not only with the link between the increase in bank loans and real economic growth but also with the issue of credit allocation across industrial sectors, or more productive branches. Over time we have observed the sunrise of some sectors and the sunset of others. For instance, in recent decades information technology and biotechnology have become more important in most economies while the importance of traditional sectors has shrunk. Countries have reacted in different ways to these trends, depending, among many other factors, on the capacity to reallocate bank credit from declining sectors to emerging ones. This capacity is particularly crucial in countries – like Italy – where the Stock Exchange has a small size. Moreover, non-bank funds – such as those granted by venture capital and private equity operators – are still limited in Italy: this reinforces the role of banks for the financing of the business sector. Economic growth, which was very poor in Italy since the 1990s, depends on the capacity of businesses to incorporate and foster innovation (Visco, 2020).The delays accumulated in innovation and education and their interrelation with the structure of the productive system are probably at the origin of Italy's weak economic growth.

The purpose of this paper is to study bank credit allocation among branches of economic activity in Italy over a long-run horizon – from 1981 to 2017. In these almost 40 years some sectors shrank

[1] De Bonis (Banca d'Italia), Ferri (Libera Università Maria Santissima Assunta, LUMSA), Forte (Centro Europa Ricerche, CER), Silipo (Università della Calabria). We thank Giuseppe Marinelli and Giorgio Nuzzo for their help in the construction of the database. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Bank of Italy and CER.

while other sectors thrived. On one hand, some of the sunset sectors were part of the typical backbone of Italy's light manufacturing industrialization of the postwar period. On the other hand, a common feature of the sunrise sectors was their high reliance on new technologies. Between 1981 and 2017 the rank of the 16 productive branches we managed to reconstruct changed significantly in terms of their contribution to Italy's total value added. The most vivid example of decline is offered by the branch Textiles, clothing and leather products, whose contribution to total value added dropped from 4.88% in 1981 to 2.06% in 2017 (Table 1). On the opposite, the strongest progress was recorded by the branch Electricity, gas, steam and air conditioning supply, whose contribution expanded from 1.05% in 1981 to 2.17% in 2017. In passing, we can note that the technology content of the branch Textiles, clothing and leather products is the lowest.

– Insert Table 1 about here –

It goes without saying that the orderly redeployment of productive capacity from shrinking to expanding sectors needed bank loans to smooth out the process. Was this the case in reality? Namely, we ask whether the allocation of bank loans was consistent with that overarching shift from light manufacturing to the sectors more ingrained to a higher technology component.

While Schumpeter (1912) was probably the first scholar to underline the key role of credit for the selection of good entrepreneurial projects, in recent years some contributions focused again on credit misallocation. The global financial crisis (GFC), the following Great Recession, the euro area sovereign debt crisis, and the failures of banks since 2007 are among the main motivations of this literature. We will not review the large literature on the nexus between finance and growth, focusing instead only on bank credit allocation.

Bleck e Liu (2018) present a theoretical model showing that excessive credit expansion can benefit lower-frictioned – in terms of collateral – industrial sectors, crowding out higher-frictioned sectors. Therefore, misallocation of credit can contribute to underperformance of the aggregate economy. Wurgler (2000) looked at the allocation of credit across 65 countries. His main conclusion is that developed financial markets, as measured by the size of the domestic stock and credit markets relative to GDP, are associated with a better allocation of capital. Financially developed countries are swifter at both increasing investment in growing industries and decreasing investment in declining industries.

Using a dataset that covers almost all bank-firm relationships in Italy in the period 2004-2013, Schivardi et al. (2017) study whether banks with low capital extended excessive credit to weak firms and if the phenomenon mattered for aggregate efficiency. They conclude that while banks with low capital can be an important source of aggregate inefficiency in the long run, their contribution to the severity of the Great Recession via capital misallocation was modest.

Cingano and Hassan (2019) study the impact of international financial flows on credit allocation exploiting the strong increase of capital inflows in Italy in the first years of the new Millennium. They find that international financial flows did not contribute to increase misallocation through the bank lending channel.

The paper that comes closest to ours is probably that by Battilossi et al. (2013). They study credit allocation across Italian industrial sectors between 1948 and 2009, assuming that an efficient allocation takes into account the variation of sectoral growth opportunities, as revealed by stock market data. Their results show that allocative efficiency was higher during the Italian postwar boom (1950s-1960s), deteriorated in the over-regulation era (1970s-1980s) and rose again with the financial liberalization of the early 1990s. However, the thrust of Battilossi et al.'s analysis may be questioned because of the fact that in Italy the size of the stock market has always been rather small throughout the studied period.

Our contribution to the extant literature is threefold. First, and preliminary to the empirical analysis, through painstaking work we build the longest and more detailed available time series of the sectoral level variables employed in our regressions. Second, through the considered nearly 40 years, we investigate whether bank loans were actually dispensed to the most deserving sectors, that is those sectors with expanding trajectories and/or more productive and/or embodying more advanced technology. Third, we test whether loan allocation was affected by institutional innovations and/or by business cycle patterns.

Our results show some nuances. On the positive side, we document that banks lent more to the sectors where value added was growing more rapidly, while loans were expanded less to more risky sectors, as captured by their higher bad loans shares. On the negative side, we uncover that the allocation of loans was negatively related – or at best insensitive – to the sectoral growth of productivity and fell short of serving the higher technology sectors. However, there are signs that the allocation of loans to the more technology-oriented sectors improved after the liberalization of the credit markets of the 1990s.

The paper is divided in 7 Sections. Following this Introduction, Section 2 accomplishes two tasks. First, it describes the many hurdles tackled in reconstructing sectoral level data and presents descriptive statistics of the time series we obtained; second, it presents the overall thrust of our empirical analysis. In Section 3, we depict the macroeconomic context and present some preliminary evidence based on graphic representations. Section 4 develops our main testable hypotheses and unfolds our regression model specifications. Section 5 reports and comments our main empirical results. In Section 6 we provide some robustness checks by investigating the links among investments, loans and productivity in the long run. Finally, Section 7 synthesizes the main conclusions, exposing key caveats and offering suggestions for future research.

2. Data and Methodology

First of all, we assembled a data set on bank loans and bank bad loans. While previous papers usually looked at the allocation of credit between only two aggregate sectors, typically households and firms, we use more disaggregated data which refer to branches of economic activity. This is a much finer classification which is available for non-financial corporations and for producer-households. Our data set spans from 1981 to 2017 and comprises the following 16 branches of economic activity:

1 Agriculture, forestry and fishing;
2 Electricity, gas, steam and air conditioning supply;
3 Basic metals, fabricated metal products and non-metallic mineral products;
4 Refined petroleum products, chemical products and pharmaceuticals;
5 Machinery and equipment;
6 Electronics products, electrical and non-electrical equipment and apparatus;
7 Motor vehicles and other transport equipment;
8 Food, beverages and tobacco products;
9 Textiles, clothing and leather products;
10 Paper, paper products and printing;
11 Rubber and plastic products;
12 Construction;
13 Wholesale and retail trade, repair of motor vehicles and motorcycles;
14 Accommodation and food service activities;
15 Transportation and storage, Information and communication;
16 All remaining activities.

In order to build our series, we matched the most recent data, from 2001 to 2017 and for the above mentioned 16 branches we managed to weld them with older series, that span from 1981 to 2008. We operated in two steps. The first elaboration has been useful for matching the actual statistical classification with the previous one, given that the branches have changed during the time. Then, in order to avoid series discontinuities, we prolonged the most recent series, that end in 2001, adopting the percentage change of the older ones for the period 1981-2001. Adopting this procedure, we assembled the series of gross bank loans and bad loans for the above mentioned 16 branches, taking into account both non-financial corporations and producer-households.

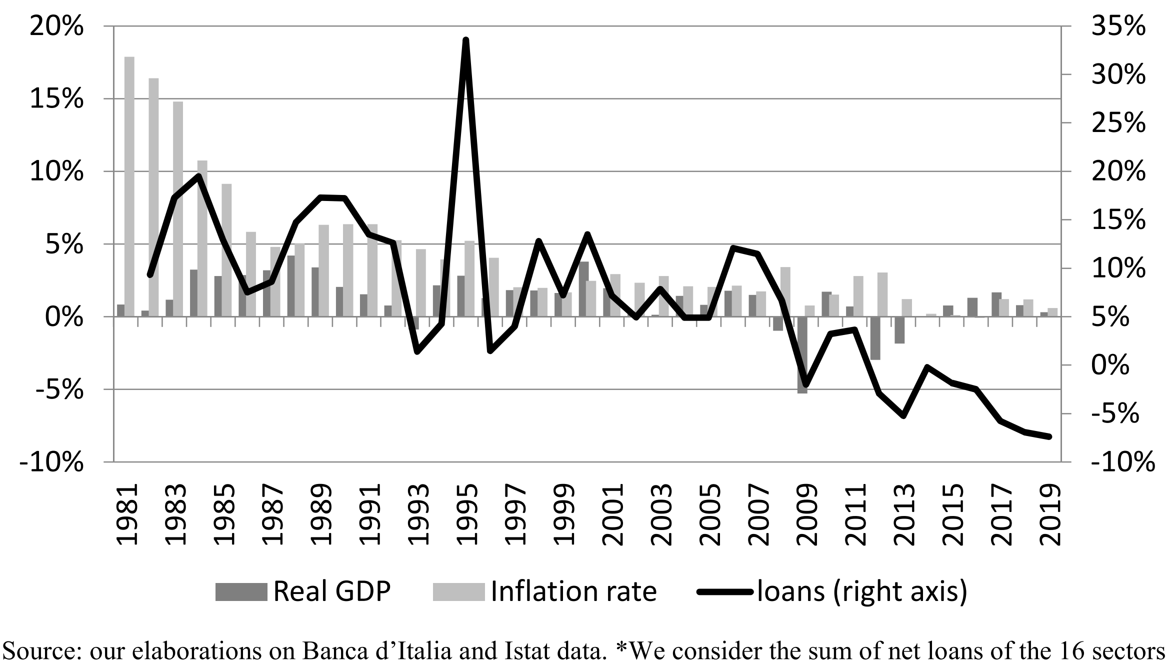
The same approach has been used also to collect non-banking series, that is: value added, number of branch employees, productivity, stock of capital and investments for each branch. Indeed, even for these data a change in classification and a discontinuity in the data set published by ISTAT exists.

Our data set is completed with macroeconomic data covering the same period: GDP real growth; inflation rate (source Istat); Banca d'Italia discount rate until 1998 and European Central Bank main refinancing operation rate since 1999; Italian banks capital and total assets (source Banca d'Italia). Only for real GDP we used the same approach seen before for reconstructing the series, while complete series are available without any discontinuity in the other cases.

Therefore, the dataset we employed is a panel with 16 branches, 37 years, 7 variables per branch and a set of 4 macroeconomic variables.

We also generate a series of dummy variables: 1) a dummy for each branch; 2) a dummy for each year; 3) a dummy for each specific time period: dummy *boom1*, from 1981 to 1991, dummy *crisis1*, from 1992 to 1995, dummy *boom2*, from 1996 to 2006, and dummy *crisis2*, from 2007 to 2017; 4) a dummy for the period 1991-2017 that covers the years after the liberalization of the Italian banking system; 5) five dummies for the different technological content of the production of each branch: dummy *tec1* for branches 1 and 2, dummy *tec2*, for branches 3 and 8, dummy *tec3* for branches 9 and 10, dummy *tec4* for branches 4, 5 and 7, and dummy *tec5* for branch 6.

Figure 1. Real GDP growth, inflation rate, loans* to 16 branches percentage change



Source: our elaborations on Banca d'Italia and Istat data. *We consider the sum of net loans of the 16 sectors (total gross loans minus bad loans). Loans are unadjusted for effect of securitization.

The five tech dummies follow the classification by Lall (2000), based on the technological content of the sectors, going from the primary products (*tec1*), resource-based manufactures (*tec2*), low-technology manufactures (*tec3*), medium-technology manufactures (*tec4*), and high-technology manufactures (*tec5*). The latter sectors are those which experienced the highest growth rates worldwide in the latest decades. So, this classification allows to investigate to what extent Italian banks supported the transition from traditional sectors to the leading sectors of the third industrial revolution. Notice that this classification does not include all the sectors and it does not take account of the large variation in technological content that may exist within each sector. However, we maintain that the differences among sectors are more relevant than those within each sector.[2]

3. Economic context and preliminary evidence

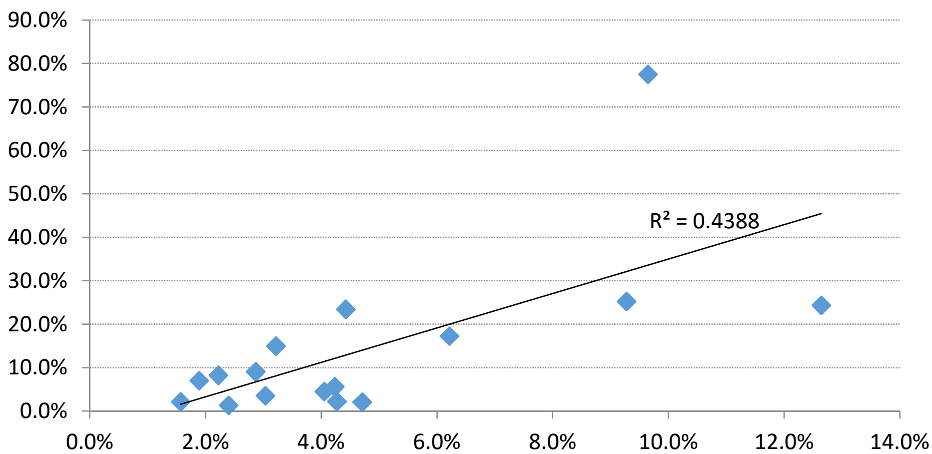
We can roughly split the nearly 40 years under investigation in four periods:

(i) Economic growth and credit growth were both high in the 1980s.

(ii) The previous phase was interrupted by the recession of 1992-93. The recession hit mostly Southern banks; some intermediaries went bankrupt while others were bailed-out, through the intervention of State funds and the acquisitions by Centre-Northern banks.

(iii) In the 1990s banking markets were liberalized. Opening of branches was liberalised in 1990. A new Banking Code was approved in 1993. Banks were progressively privatised. The changes in regulation ended the "financial repression era" introduced in the 1930s, as a consequence of the Great Depression, and lasted until the 1980s (see De Bonis et al., 2018). After the explosion of bad loans caused by the 1992-93 recession, credit allocation and credit quality improved. Credit growth was satisfactory – in line with the euro area average – from the second half of the 1990s until the eruption of the GFC in 2007-2008.

Figure 2. Relationship between value added and loans, 16 sectors.



Note: y = loans percentage change 1981-2019, x = value added percentage change 1981-2019. Metallurgical, paper and plastics industries 1981-2017.

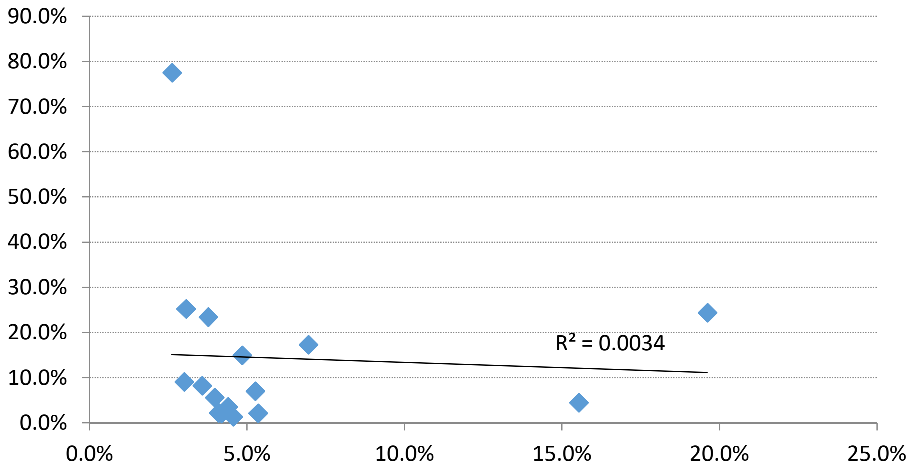
(iv) The Italian economy was hit by the GFC; in 2009 the contraction of GDP was the strongest since the end of the Second World War. Following the brief recovery of 2010, the euro area debt sovereign crisis hit Italy since the second half of 2011. The economy was in recession until 2013. Many firms failed and a credit crunch took place. Credit growth to

[2] For our purpose, this classification is superior to Pavitt (1984). This author distinguishes between resource-based, labor-intensive, scale-intensive, differentiated and science-based manufactures. This classification is difficult to use because the analytical distinctions are unclear and there are large overlaps between categories (Lall, 2000). In addition, Amatori et al. (2011) consider the failure to adopt the new technologies the main problem of the Italian economy.

the private sector was negative from the second half of 2012 to 2015. The growth of credit improved from 2016. Overall the Great Recession (2007-2013) was in Italy worse than the Great Depression (1929-1936) in terms of contraction of real GDP, investments and consumption. During the Great Recession credit quality worsened but bank failures were less frequent and less intense than during the Great Depression (De Bonis et al., 2020).

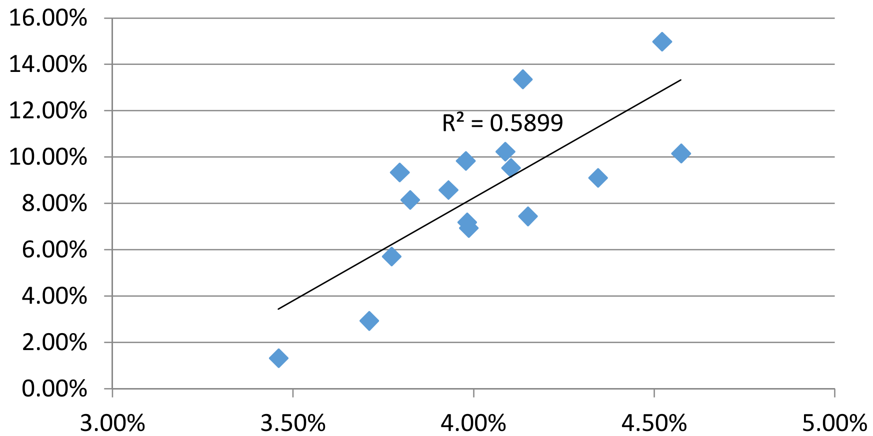
While it is not easy to see a clear association at the aggregate level between growth rates of loans and the rate of growth of GDP and the inflation rate, Figure 1 helps detect some response in terms of loan growth in correspondence of business cycle expansions, such as in the late 1980s; around 1994-95, assisting the recovery from the 1992-93 recession; and in 2005-07, before the eruption of the GFC. The picture also shows the consequences of the recessionary phases, for instance in 1992, 2009, and 2012-13. It is also comforting to notice that sectoral data identify a positive relationship between the percentage change of loans and that of value added throughout the four examined decades (Figure 2).

Figure 3. Relationship between productivity and loans, 16 branches



Note: y = loans percentage change 1981 2019, x = productivity percentage change 1981 2019. Metallurgical, paper and plastics industries 1981-2017

Figure 4. Relationship between interest rates and bad loans to total loans ratio, 16 branches

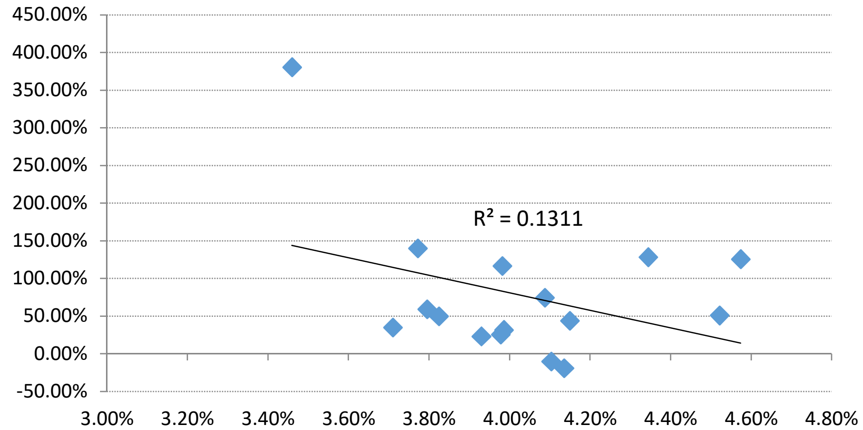


Source: y = average bad loans to total loans ratio, 1998 - 2018, x = average interest rate on loans, 1998 – 2018.

However, we note that, on branch data, the relationship between the percentage change of loans and that of productivity is slightly negative throughout the period (Figure 3).

At the same time, we see that, on sectoral data, the relationship between interest rates on loans and bad loans ratios is strongly positive through the nearly 20 years (Figure 4) – suggesting that, overall, credit risk was correctly priced by banks – while loans increased more to the sectors that were paying lower loan rates (Figure 5).

Figure 5. Relationship between interest rates and loans, 16 branches



Source: y = loans percentage change, 1998 - 2018, x = average interest rate on loans, 1998 - 2019.

4. Hypotheses and Regression Models Specifications

In the last forty years, the most advanced economies underwent two main structural changes. First, they experienced a rapid increase of the relevance of the most intensive technological sectors. Second, advanced economies lost market shares in low-medium technological sectors, to the advantage of the emerging economies. As said, our statistics show the same shifts in Italy.

The capability of the financial system of a country to reallocate finance from declining to the expanding and more innovative sectors has a major impact on the macroeconomic performance of the country.

The correlation between allocation of finance and sectorial performance indicators is relevant both whether finance spurs the growth of the more innovative sectors or it follows the latter, by supporting the sectors that proved to be more capable to grow and innovate.

We investigate the nexus between finance and sectorial growth in a bank-based financial system, where loans are the main or the only source of finance for firms. In this context, we study the allocative efficiency of the banking system of the country in a long run perspective, by addressing to what extent the allocation of loans among sectors is in line with the growth of value added, productivity and technological intensity of the sector.

In detail we test three hypotheses.

Hypothesis 1. Banks allocate a higher proportion of loans to the most productive sectors, accounting for firms' risks.

There is evidence that better opportunities for investment exist in sectors with higher increase of value added and productivity than in declining sectors. Wurgler (2000) shows that in most developed countries investments increase more in the expanding sectors and decrease more in the declining sectors. Rajan and Zingales (1998) provide further evidence that firms are more capable to exploit the opportunity for growth in countries with more developed financial systems. In addition, Fishman and Love (2004) examine the role of financial market development in intersectoral allocation when there exist common global shocks to growth opportunities. They prove that two countries have more highly correlated growth rates across sectors when both countries have well-developed financial markets. Consequently, banks' allocative efficiency implies their capability to reallocate loan portfolios from sunset to sunrise sectors or to sectors with higher opportunities for investment.

Banks use several criteria to allocate loans, and the expected revenue of the investment may not be the only determinants or even the most important ones. Risk, size, age, collaterals, liquidity, leverage of a firm or relationship lending may be more relevant than the allocation of loans to the most productive sectors (Schiantarelli et al., 1996). Dörr et al. (2017) examine the implications for firm productivity of adverse shocks to bank lending in Italy, and find a negative shock to bank credit supply reduces firms' loan growth, investment, capital-to-labor ratio, and productivity. But Linarello et al. (2018) find for the period 2000-2015 only a negligible effect of credit shocks on aggregate productivity of the Italian firms. By contrast, Hassan et al. (2017) show that capital misallocation by banks can be a key driver of the long-standing slow productivity growth that characterizes Italy and other periphery countries. And Calligaris et al. (2016) find that the extent of misallocation has substantially increased since 1995.

By relying on firm level data, the cited papers may bestow stronger identification underpinnings compared to our sector-level analysis. At the same time, those papers use data for much shorter periods than the long-term period our sectorial data allow investigating and, thus, our methodology may be superior in terms of identifying long-run trends.

We posit that the banking system of the country allocates a higher proportion of loans to those sectors with better relative performance in terms of value added and productivity. The increase in total loans to the sector may precede or follow the increase in value added and productivity of the sector. However, the higher the capability of the banking system to spur the most dynamic and productive sectors the stronger is the role of banks in supporting the transition of the economy to new technological paradigms.

We test the above hypotheses by the following equation:

$$\Delta(L_s/L)_t = \alpha_0 + \alpha_1 \Delta \frac{VA_s/N_s}{VA_t/N_t} + \alpha_2 \Delta(VA_s/VA)_t + \alpha_3 \Delta(\mathrm{NPL}_s/\mathrm{NPL})_t + \alpha_4 (\mathrm{KAPITAL/Total\ Assets})_t + \alpha_5\, tec1 + \alpha_6\, tec2 + \alpha_7\, tec3 + \alpha_8\, tec4 + \alpha_9\, tec5 + \alpha_{10} GROWTH_t + \alpha_{11} INFL_t + \varepsilon_{st} \quad \textbf{(1)}$$

The dependent variable is the yearly change of the ratio between loans to each sector and loans to all sectors. The first regressor is the delta of the ratio of the sectorial labor productivity relative to total productivity; the second independent variable is the delta of the ratio of value added relative to total value added, while the third is the delta of the ratio of non-performing loans of the sector relative to all sectors. KAPITAL/Total Assets is a measure of the capability of banks to provide loans, while the dummies capture the technological content of the sectors, going from the lowest (tec1) to the highest (tec5) technological-content sectors. The latter are those with the highest opportunities for growth. We expect that the coefficients α_1 and α_2 are positive and significant, reflecting higher support of the banks to the most productive sectors. In addition, we expect the sign of α_5 and α_6 to be negative, while the coefficients α_8 and α_9 to be positive, based on the assumption that in this period banks switched loans from low-tech to the high-tech sectors.

Hypothesis 2. Banks increase lending more to high-tech than low-tech sectors.

In the period under investigation, the opportunities for investment in the world economy shifted from low-medium tech sectors to high-tech sectors (i.e., electrical machineries and electronics, telecommunication, biotechnology, etc.). So, a great deal of opportunities for growth of the Italian economy were determined by the capabilities to adapt to this technological shift.

The common view (Battilossi et al., 2011) is that the Italian economy managed grasping the growth opportunities generated by the global technological shocks up to the 1970s, but this capability weakened starting from the 1980s (the period of our investigation). More precisely, Battilossi et al. (2011) investigate the link between bank loans and opportunities for growth of the sectors (measured by stock prices over earning of the sector) for the Italian economy in the period 1948-2009.They find that the coefficient of cointegration of the two variables is positive and significant only in the periods 1948-1970 and 1995-2009, but not in the period 1971-1994.

Consistent with the view that banks shifted in this period the allocation of loans from low- to high-tech sectors, we expect in the equation below that the coefficients for dummies 4 and 5 are positive, and for dummies 1 and 2 are negative.

$$\Delta\%L_{st} = \alpha_0 + \alpha_1\Delta\%\frac{VA_{st}}{N_{st}} + \alpha_2\Delta\%VA_{st} + \alpha_3\Delta\%NPL_{st} + \alpha_4(\text{KAPITAL/Total Assets})_t + \alpha_5\, tec1 + \alpha_6\, tec2 + \alpha_7\, tec3 + \alpha_8\, tec4 + \alpha_9\, tec5 + \alpha_{10}DR_t + \alpha_{11}GROWTH_t + \alpha_{12}INFL_t + \varepsilon_{st} \quad \textbf{(2)}$$

$\Delta\%$ is percentage change of the variable.[3]

Even though in the above equations we assume that the allocation of loans is affected by the relative performance of the sectors, it may be also the case that the former determines the latter. Hence, we performed Granger causality tests on equations 1-2 above. On the other hand, the allocation of loans is more likely to be determined by the supply side conditions, if structural changes occur in the financial system.

Indeed, there is large evidence that the nature of banks as well as market structure and regulations are important determinants of allocative efficiency. In the 1990s the Italian banking system underwent major changes, following the liberalization and privatization of the main banks. So, our data allow to investigate whether the Italian banking system had a more active role in the developments of the Italian economy after the implementation of the new banking reforms.

Hypothesis 3. Liberalization and privatization of banks increases the allocation of loans to the most productive sectors.

Studies on both emerging markets (Jaramillo et al., 1995; Galindo et al., 2007) and developed countries (Laeven, 2003) provide evidence that financial markets' liberalization improves allocative efficiency and reduces credit rationing. Battilossi et al. (2011) confirmed these conclusions with respect to the effects of liberalization and privatization of Italian banks, by showing that after 1990 the allocation of loans across sectors is more in line with the growth opportunities of the sectors.[4]

In the previous equations we established a direct link between credit and sectorial productivity. However, the latter is determined by investments and innovations. Hence, an efficient allocation of loans implies that there is also a positive correlation between loans to a sector and the amount of

[3] Equation 2 is based on less stringent assumptions about loan portfolio allocation. Equation 1 assumes that banks allocate loans to each sector in order to equate expected returns in each sector. By contrast, equation 2 assumes that banks react to change in expected revenue of one sector irrespective to revenues in the other sectors.

[4] However, the new banking law expanded also the scope of operation of the banks, which may have also increased the incentive to switch from lending to other activities.

investment and innovation of the sector. By contrast, zombie lending (see Caballero et al., 2006, Schivardi et al., 2017) may depress the investment and employment growth of non-zombie sectors and widen the productivity gap between zombie and non-zombie sectors. So, following among others Caggese (2016) and Manaresi and Pierri (2017), we assume there is a direct effect of credit on firm's investments.

We test the correlation between lending and investments by the following:

$$\frac{INV_{st+1}}{INV_{st}} = \alpha_0 + \alpha_1 \frac{VA_{st}}{VA_{st_{st-1}}} + \alpha_2 \frac{LOANS_{st}}{LOANS_{st-1}} + \varepsilon_t \qquad \textbf{(3)}$$

Equation 3 assumes that investments in each sector can be financed by internal funding (proxied by the increase in the realized value added of the sector) and by bank loans. We posit that an increase of both sources of funding spurs investments. But if banks in a prolonged depression misallocate credit to weak firms operating in declining sectors (zombie lending), loans may not have a significant impact on investments.

A more clear-cut picture of the role of finance for growth may emerge when we analyze lending to innovative activities. Indeed, innovations deal only with those activities capable to create new markets or more efficient methods of production, which have a greater impact on growth.[5]

To study the effects of bank lending on the amount of innovation of the sector, first we estimate the aggregate production function by sector, and then we use the estimated Solow residual of each sector to test the following relationship:

$$\triangle \text{RESIDSOLOW}_{st+1} = \alpha_0 + \alpha_1 \triangle \boldsymbol{LOANS_{st}} + \alpha_2 tec1 + \alpha_3 tec2 + \alpha_4 tec3 + \alpha_5 tec4 + \alpha_6 tec5 + \alpha_7 GROWTH\text{t} + \alpha_8 INFL\text{t} + \varepsilon_t \qquad \textbf{(4)}$$

We assume that the increase in bank loans spurs the amount of innovation of the sector, measured by the Solow residual. Manaresi and Pierri (2017), using a matched bank-firm panel data covering the period 1998-2012, show that an expansion of credit supply to Italian manufacturers' production increases both input accumulation (size effect) and the ability to generate value added for a given level of inputs (productivity effect).

However, several other factors may affect the relationship between loans and investments. One is the different need for external finance across sectors.

To investigate this issue, we performed the following exercise (see Section 6). Rajan and Zingales (1998) built up an index of the need of external finance for the industrial sectors of the US economy. Assuming that the dependence from external finance is similar for the Italian sectors, we studied whether the allocation of loans by Italian banks is in line with the need of external finance of the sectors. Among other things, this methodology offers additional insights on the allocation of loans between high and low-tech sectors in the last forty years of the Italian economy.

5. Main Results

We attempt to uncover the possible relationship over time between the allocation of bank loans, on one hand, and, on the other, the evolution of sectoral performance indicators as well as sectoral

[5] Indeed, innovations are riskier and more rewarding activities, and the financing of innovation depends on the average degree of risk-aversion of the banks.

specific identifiers. The evolution of bank loans through time is described by one of the following two (see Table 2 for a list and definitions of all the variables and their basic descriptive values):

i) the change in the share of the total loans accruing to a specific sector *i* at time *t*, $DLSH_{it} = \Delta(Loan_{it}/Loan_t)$, where $Loan_{it}$ is loans to the sector and $Loan_t$ is total loans to all sectors;
ii) the percentage rate of growth of loans to a specific sector *i* at time *t* ($DPLOAN_{it}$).

The relevant sector-level regressors we consider are the following:

- the change in the share of the value added in a specific sector *i* at time *t*, $DVARAT_{it} = \Delta(VA_{it}/VA_t)$, where VA_{it} is the value added of the sector and VA_t is total value added of all sectors. $DVARAT_{it}$ aims to capture the relative ability of a sector to create value added – be it because of its efficiency, innovativeness, market power or else – which could be viewed as a proxy of the sector's ability to pay back the loans it receives;
- the change in the ratio of labor productivity in a sector to average labor productivity across all sectors, $DNPRODRAT_{it} = \Delta[(VA_{it}/N_{it}) / (VA_t/N_t)]$, where N_{it} (N_t) is the number of employees of the sector (across all sectors). $DNPRODRAT_{it}$ measures the change in relative labor productivity of a sector which could be viewed as a proxy of the sector's efficiency;
- the change in the share of the bad loans in a specific sector *i* at time *t*, $DBADLRAT_{it} = \Delta(BADL_{it}/BADL_t)$, where $BADL_{it}$ is bad loans of the sector and $BADL_t$ is total bad loans of all sectors. $DBADLRAT_{it}$ aims to capture the ex post relative risk of a sector which could discourage banks from lending to that sector;
- the percentage rate of growth of value added in a specific sector *i* at time *t* ($DPVA_{it}$);
- the percentage rate of growth of labor productivity in a specific sector *i* at time *t* ($DNPROD_{it}$);
- the percentage rate of growth of bad loans to a specific sector *i* at time *t* ($DPBADL_{it}$);
- a set of dummies – TEC1, TEC2, TEC3, TEC4, TEC5 – identifying the more technically innovative sectors.

We also include some macroeconomic or system-level variables as follows:

- the rate of inflation ($INFL_t$);
- the rate of growth of real GDP (RGG_t);
- the banking system's capital/asset ratio ($CAPASSRAT_t$), where $CAPASSRAT_t = CAP_t / ASS_t$ with CAP_t being total capital and ASS_t being total assets;
- the change of the banking system's capital/asset ratio ($DCAPASSRAT_t$);
- the percentage rate of growth of the banking system's capital/asset ratio ($DPCAPASSRAT_t$);
- a dummy variable marking the liberalization of the Italian banking system (LIB_t=0 until 1989 and LIB_t =1 from 1990);
- three dummy variables singling out major deviations from the GDP trend: CRISIS1 represents the 1992-1995 period, BOOM covers the 1996-2006 period and CRISIS2 is the dummy for the period 2007-2019;
- five dummy variables – TEC1, TEC2, TEC3, TEC4, TEC5 – identifying the sectors which express a higher technological content, where the tech content supposedly increases from 1 to 5;
- the Bank of Italy discount rate and the ECB main refinancing operations rate (DR).

– Insert Table 2 about here –

Relating to Hypothesis 1 and Equation 1, the results obtained in our regressions lend themselves to easy interpretations. Namely, the change in the share of loans accruing to the individual sector (DLSH) seems to respond positively and significantly to the change in the share of value added of the sector on total value added (DVARAT) – as found for Model 1 and Model 2 – but not to the more relevant change in the ratio of labor productivity in a sector to average labor productivity across all sectors (DNPRODRAT) – as shown in for Model 3 and Model 4 (Table 3). Thus, there is no strong support for our Hypothesis 1.

For the other covariates, we can notice that the change in the share of the bad loans in a specific sector (DBADLRAT) turns out positively and significantly related to DLSH for the first three Models – the difference between Model 1 and Model 2 is that DBADLRAT is lagged in Model 2 – but not for Model 4. GDP growth (RGG) and inflation (INFL) are not significantly related to DLSH. Regarding the tech dummies (TEC1, TEC2, TEC3, TEC4, TEC5) they are often significant and negative, suggesting that loan shares have generally increased less in the technologically advanced sectors. Thus, there is no support for our Hypothesis 2.

The Crisis and Boom dummies are not statistically significant per se, but when we interact them with DVARAT – the same does not hold for DNPRODRAT – results show that the growth of DLSH was significantly lower during the two crisis periods identified by CRISIS1 and CRISIS2. Finally, in Model 4, the dummy capturing the possible time break due to the liberalization of the credit market since 1990 (LIB) is significantly related to DLSH but bears a counterintuitive negative sign, suggesting that loan sector shares did not increase more after the liberalization. Nevertheless, it is interesting to observe that, once interacted with the tech dummies, LIB deploys positive and significant effects, hinting that loan sector shares have increased more in the technology intensive sector after the banking liberalization. This last evidence provides moderate support for our Hypothesis 3.

Although all the models seem to be appropriate – as evidenced by the F statistics – their goodness of fit is low, as shown by the very low R-squares.

– Insert Table 3 about here –

A specific issue here and below is the potential endogeneity between the dependent and explanatory variables, which might lead to biased and inconsistent parameter estimates. We tested the presence of endogenous regressors via Hausman tests[6] and found endogeneity in 5 out of 6 regressors tested. Hence, we re-estimated all our models (models labeled with -B) by replacing the initial regressors with substitute variables. For each initial variable, we obtained the new regressor by calculating the mean value of the same variable of all the other branches belonging to the same technological sector.[7]

Looking at Table 4, we are now focusing on Hypothesis 2 and Equation 2 and can notice that some of the findings shown for DLSH carry over to the growth of sectoral loans (DPLOAN). Specifically, in Model 5 DPLOAN associates positively and significantly with DPVA, the sectoral growth of value added, albeit neither with DNPROD, the sectoral growth of value added per employee, nor with the growth of our ex-post measure of risk, DPBADL. Again, there is no strong support for our Hypothesis 1. The TEC dummies are negatively associated with DPLOAN, some of them reaching significant levels, suggesting that the allocation of sectoral loans does not seem to have favored the more technologically oriented sectors. Once more, there is no support for our Hypothesis 2.

[6] To carry out the test we re-estimated our models using all the independent variables, in turns, as dependent one. We then used residuals of these models as regressors in the original equations in order to check if the residuals were significant.

[7] To have large enough groups, we merged the Tec1 and Tec2 groups and the Tec 3, Tec 4 and Tec 5 groups. In this way every variable of a sector belonging to Tec1 or Tec2 groups has been substituted by the average values of the other sectors included in Tec1 and Tec2. The same procedure was used for branches in the other technological groups. For example, instead of using the change in bad loans of the agricultural sector, we employed, as regressor for agriculture, the change in the sum of bad loans of all other sectors belonging to the Tec1 and Tec2 groups. The same approach was applied to every sectoral variable. This approach was previously used by Caprio et al. (2007) and Laeven and Levine (2009).

In this model as well as in all the subsequent ones, we notice that: i) INFL is positively ad significantly associated with DPLOAN, bearing a relatively stable coefficient; ii) the goodness of fit is much higher than for the models of Table 3. The only change of Model 6 with respect to Model 5 consists in introducing the change in the capital/asset ratio of the banks (DCAPASSRAT), which turns out positive and significant, as expected.

Model 7, instead, considers the possibly different behavior over the three time periods characterized by pronounced output volatility, CRISIS1, BOOM, and CRISIS2. Although the three dummies seem rather insignificant – only CRISIS2 reaches statistical significance and just at 10% – it is interesting to note that the interaction of DPVA with these dummies is positive and significant, while this associates with a significant but negative coefficient of DPVA. Moreover, the size of the coefficient of DPVA per se is always smaller than the size of the coefficients of its interactions with the dummies. This hints that banks seem to have favored high-value-added-growth sectors mostly during the time periods of more intense output variation. These latter results apply also to Model 8, whose main innovation with respect to Model 7 consists in introducing the TEC dummies as well. Indeed, the effect of the TEC dummies is analogous to what detected in Model 6.

In turn, the two main innovations of Model 9 regard abandoning DPVA in favor of DNPROD, the growth of value added per employee, and the introduction of the dummy LIB and of its interactions with the TEC dummies, as previously done in Model 4. This time around, DNPROD is significant but negative, suggesting that the allocation of credit does not favor the sectors with high DNPROD. A more encouraging finding, here, is that DPBADL is not only negative but also significant – albeit at 10% only – implying that banks have lent less to riskier sectors. Alongside, the results for the TEC dummies, the LIB dummy and the interactions among the two turn out more or less analogous to what found for Model 4. Again, this last evidence provides moderate support for our Hypothesis 3.

– Insert Table 4 about here –

Overall, the results of these regressions find both shadows and lights. The shadows are that banks' allocation of credit seems to have favored neither the sectors where productivity – value added per employee – was increasing above average nor the sectors featuring higher technological content – which are normally expected to enjoy higher competitiveness.[8] However, we found also some lights. Namely, the allocation of credit does not seem to have been systematically higher in more risky sectors – along the possible hypothesis of banks financing zombie firms (Acharya et al., 2019) –, on the contrary, at times we detect that banks reduce loan extension to more risky sectors. Moreover, banks appear to have generally increased their lending to the TEC sectors after the banking liberalization. Finally, the orientation of credit to the high-value-added-growth sectors has intensified during the phases of more pronounced output variation, which are the times when credit is more needed for either expanding or restructuring, consistently with the view that banks grant flexibility in the use of their loans, rather than causing a credit crunch.

6. Investments, loans and productivity in the long run

Here we perform further cross-branch analyses on how the allocation of bank loans relates to investment, productivity and external finance dependence. These further analyses may offer additional robustness checks to our previous findings.

In the first place, we follow up on Equation 3 and study the possible relationship between investments and bank loan dynamics. The results of the regression estimates are reported in Table 5. They show that the dynamics of investments is generally unrelated to that of bank loans and, in

[8] Consistent with this conclusion, Coccorese and Silipo (2015) find that between 1980 and 2010 the great expansion of Italian financial markets and institutions did have a positive effect on regional economic performance, but overall growth rates were nevertheless low.

Model 1B, it even emerges a significant negative association between the two variables. The prevailing evidence from this specification seems to corroborate the results commented in the previous Sections. In other words, no strong role emerges for bank loans in promoting investment.

– Insert Table 5 about here –

Secondly, we consider that the dynamics of value added and even that of labor productivity are variables that can be improved to measure the true growth potential. Specifically following the literature, we run a growth regression where the regressors are the capital and labor inputs at the branch level. From this regression, it is possible to estimate the Solow residuals – representing the growth of value added not accounted for by changes in either capital or labor – usually associated with technical progress. The results of this regression estimates are reported in Table 6, where naturally both explanatory variables are highly significant and together are able to explain a noticeable part of the variance of the dependent variable, as revealed by the relatively high R^2.

– Insert Table 6 about here –

Next, we run a regression to assess the relationship between the Solow residuals and the dynamics of bank loans to the sector, together with other control variables. The results, reported in Table 7, show that the dynamics of bank loans is negatively associated with the dependent variable, which is instead positively linked with GDP growth, with inflation, and with the dummy TEC1. Thus, it seems that bank loans were not allocated to the branches with higher growth potential, as identified by larger Solow residuals. A caveat is in order here. Namely, the finding that only low level of technology – TEC1 is the dummy identifying the lowest technology component – seem to enhance the Solow residuals is somewhat counterintuitive. In any case, the evidence from this specification seems to corroborate the results commented in the previous Sections. In other words, no strong role emerges for bank loans in promoting technological progress.

– Insert Table 7 about here –

In addition, an alternative approach to assess the link between finance and growth is provided by Rajan and Zingales (1998). They build up an index of the need of external finance for the US industrial sectors, and they show that sectors or firms more in need of finance are more likely to growth in more developed financial systems. In addition, they provide a few reasons why external finance in the same sectors in other advanced countries is similar to the US (see Rajan and Zingales, 1998). Hence, assuming that similar sectors in Italy have similar financial needs than in the US, we classified sectors according to their financial needs, and we computed to what extend the sectors more in need of external finance are also those which received the highest amount of loans relative to investment expenditure. Among other things, this methodology offers additional insights on the allocation of loans between high and low-tech sectors in the last forty years of the Italian economy.

External dependence is the fraction of capital expenditures not financed with cash-flow from operations. So, using the external dependence indicators reported in Table 1 of Rajan and Zingales (1998), we built up dependence indexes for nine branches of the Italian industrial sector.

In addition, we constructed the ratio of loans over fixed investments, as a proxy of banking support to the branch. We expect that the demand for investment is equally accommodated by banks if branches more in needs of external finance are also those receiving more loans relative to their investments. So, we classify branches according to their relative intensity of financial dependence and the relative value of loans/fixed investments. The results are reported in the following table.

– Insert Table 8 about here –

The general conclusion from Table 8 is that branches with greater external finance dependence are not those receiving greater support from the banks. Indeed, leather, footwear and textile branches are among the last in external financial needs, but they get the highest support from the Italian banking system. By contrast, those with greater external dependence are among those less supported by the banks (drugs, electrical machineries, etc.). Overall, the rank correlation of external dependence and share of loans received is strong and negative (equal to –0.688) though the small number of branches (9) for which it was possible to reconstruct the matching with Rajan-Zingales does not allow to tell whether this correlation is statistically significant. Incidentally, the branches with greater external dependence are also those with the highest technological content. Indeed, the rank correlation of the two variables is strong and positive (equal to 0.642) even though, for the reason just mentioned, it is impossible to tell if this correlation is statistically significant. The last result sheds additional light on the econometric evidence above, showing an adverse effect of technological content on bank lending to the branch.

Finally, we performed a set of Granger causality tests to ascertain whether any causality links could be inferred between pairs of the main variables considered in our analysis. The results, reported in the Appendix, allow us to identify, first, the existence of a Granger causality going:

- at macro level, from growth of GDP (RGG) to growth of total loans (DPLOAN) – lag 2;
- in a sector, from labor productivity growth (DNPROD) to growth of loans (DPLOAN) – lag 2.

Second, we identify feedback effects – i.e., both variables reinforce each other in a sector – for:

- the changes in the shares of bad loans (DBADLRAT) and of total loans (DLSH) – lag 2;
- the changes in the shares of value added (DVARAT) and of total loans (DLSH) – lag 2;
- growth of value added (DPVA) and growth of loans (DPLOAN) – lag 2;
- growth of loans (DPLOAN) and labor productivity growth (DNPROD) – lag 1;
- labor productivity growth (DNPROD) and growth of loans (DPLOAN) – lag 4.

Third, we identify the other three pairs as mutually unrelated in a sector for:

- growth of bad loans (DPBADL) and growth of loans (DPLOAN) – lag 2;
- growth of value added (DPVA) and labor productivity growth (DNPROD) – lag 2;
- labor productivity growth (DNPROD) and growth of loans (DPLOAN) – lag 3.

To sum up, the Granger causality results generally support the view that bank loans are following impulses from the real economy – both GDP growth and, within a sector, labor productivity growth – or moving together in the various identified feedback links.

7. Concluding remarks

Economic growth over time demands the evolution of the productive system from sun setting to sunrise sectors. Finance is one of the main drivers to enable such evolution in the specialization of production. Thus, it is paramount that finance goes to sunrise productive branches embodying more technology and so higher growth potential. Is this requirement certified by the actual experience?

Since Italy's financial system is bank-based, we addressed this issue by studying the long-run allocation of bank loans looking at the financing of branches of economic activity in the last 40 years.

We built the longest and more detailed available time series of the sectoral level variables. Then we investigated whether bank loans were actually dispensed to the most deserving sectors, that is those sectors with expanding trajectories and/or more productive and/or embodying more advanced technology. Moreover we tested whether loan allocation was affected by institutional innovations and/or by business cycle patterns.

Our results show some nuances. On the positive side, banks lent more to the sectors where value added was growing more rapidly while loans were expanded less to more risky sectors, as captured by their higher bad loans. On the negative side, we uncover that the allocation of loans was negatively related – or at best insensitive – to the sectoral growth of productivity and fell short of serving the higher technology sectors. However, there are signs that the allocation of loans to the more technology-oriented sectors increased after the liberalization of the credit markets of the 1990s.

The general thrust of the previous claims has been further supported by alternative specifications which we have performed in relating bank loans to investments, or to the Solow residuals, as well in taking the branch allocation of bank loans to the test of the index of external finance dependence proposed by Rajan and Zingales (1998). Instead, the Granger causality analysis led to a more benevolent view on the link between branch growth and bank loans.

Overall, our assessment leads us to conclude that banks were rather following than leading productive transformations, but managed to avoid large scale misallocation of credit. Hence, we give banks just a pass grade.

Although we cannot claim that our results are wholly generalizable, the case of Italy might have implications for other bank-based financial systems. Indeed, extending the study to other countries would be an interesting avenue for future research.

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Table 1. Percentage shares of value added by sectors

Percentage of value added by sectors				
	1981	2017	Change	%Change
Agriculture, forestry and fishing	6.84%	3.15%	-3.69%	-54.0%
Electricity, gas, steam and air conditioning supply	1.05%	2.17%	1.11%	105.9%
Basic metals, fabricated metal products and non-metallic mineral products	7.76%	4.09%	-3.68%	-47.3%
Refined petroleum products, chemical products and pharmaceuticals	2.19%	1.74%	-0.46%	-20.9%
Machinery and equipment	3.42%	3.11%	-0.31%	-9.1%
Electronics products, electrical and non-electrical equipment and apparatus	2.51%	1.61%	-0.90%	-35.9%
Motor vehicles and other transport equipment	3.42%	1.89%	-1.53%	-44.7%
Food, beverages and tobacco products	2.89%	2.33%	-0.56%	-19.5%
Textiles, clothing and leather products	4.88%	2.06%	-2.82%	-57.8%
Paper, paper products and printing	1.23%	0.85%	-0.38%	-31.0%
Rubber and plastic products	1.24%	1.07%	-0.17%	-13.8%
Construction	8.93%	5.38%	-3.55%	-39.8%
Wholesale and retail trade, repair of motor vehicles and motorcycles	17.59%	15.18%	-2.41%	-13.7%
Accommodation and food service activities	3.11%	4.95%	1.84%	59.3%
Transportation and storage, Information and communication	10.48%	12.03%	1.55%	14.8%
All remaining activities	22.46%	38.42%	15.96%	71.1%
	100.00%	100.00%		

Table 2. Descriptive Statistics

Panel A – Dataset

Variable - abbreviation	Description, unit of measure, sample	Source
Loans - LOAN	Total net loans to 16 sectors, millions of euros, current values, 1981-2017	Banca d'Italia
Bad loans - BADL	Gross bad loans of 16 sectors, millions of euros, current values, 1981-2017	Banca d'Italia
Value added - VA	Value added at factor costs of 16 sectors, millions of euros, current values, 1981-2017	Istat
Employees - N	Total employees, thousands, 1981-2017	Istat
Assets - CAPSEC	Stock of non financial assets of 16 sectors, millions of euros, current replacement cost, 1981-2017	Istat
Investments - INVSEC	Gross fixed capital formation of 16 sectors, millions of euros, 1981-2017	Istat
Real GDP - RG	Gross domestic product of Italy, costant value-2015 base year, millions of euros, 1981-2017.	Istat
Capital and reserves – CAP	Italian banking system Capital and reserves, millions of euros, current price, 1981-2017	Banca d'Italia
Total asset – ASS	Italian banking system total asset, millions of euros, current price, 1984-2017	Banca d'Italia
Inflation - INF	Rate of inflation, index 2015=100, 1981-2017.	Istat
Discount rate – DR	Bank of Italy discount rate and European Central Bank m.r.o. rate, value in percent , 1981-1998 and 1999-2017.	Banca d'Italia and European Central Bank

Panel B – Dependent and independent variables statistics

Variable name	Description - formula	N.obs.	Min.	Mean	Max.	St. Dev.
DLSH	The change in the share of the total loans accruing to a specific sector, $\Delta(Loan_{it}/Loan_t)$	576	-0.0676	1.23E-18	0.1052	0.0072
DPLOAN	The percentage rate of growth of loans in each sector % $Loan_{it}$	576	-54.6955	7.7107	152.5962	16.5946
DPLOAN – table 5 model 1-B instrument	The percentage rate of growth of loans in all sectors within the same technological group of the instrumented one % $Loan_{it}$ – instrument	576	-22.5966	6.8285	97.0347	10.1817
DNPRODRAT	The change in the ratio of labor productivity in a sector to average labor productivity across all sectors $\Delta[(VA_{it}/N_{it}) / (VA_t/N_t)]$	576	-0.3561	0.0508	0.7434	0.0840
DNPRODRAT – model B instrument	The change in the ratio of labor productivity in sectors within the same technological group of the instrumented one to average labor productivity across all sectors $\Delta[(VA_{it}/N_{it})/(VA_t/N_t)]$ - instrument	576	-0.1014	0.0003	0.0865	0.0202
DVARAT	The change in the share of the value added in a specific sector $\Delta(VA_{it}/VA_t)$	576	-0.0078	0.0000	0.0148	0.0024
DVARAT – model B instrument	the change in the share of the value added in sectors within the same technological group of the instrumented one $\Delta(VA_{it}/VA_t)$ - instrument	576	-0.0059	6.25E-05	0.0108	0.0023
DBADLRAT	the change in the share of the bad loans in a specific sector $\Delta(BADL_{it}/BADL_t)$	576	-0.0669	-6.28E-19	0.0615	0.0090
DBADLRAT - model B instrument	the change in the share of the bad loans in sectors within the same technological group of the instrumented one $\Delta(BADL_{it}/BADL_t)$ - instrument	576	-0.0515	-0.0006	0.0422	0.0083
RGG	the rate of growth of real GDP %RG	576	-5.2809	1.1935	4.1944	1.8524
INFL	Rate of inflation, annual percentage change %INF	576	-0.1	2.8645	16.3934	3.6740
DPVA	the percentage rate of growth of value added in a specific sector	576	-20.7119	4.7999	75.0019	7.0101

	$\%VA_{it}$					
DPVA – model B instrument	the percentage rate of growth of value added in all sectors within the same technological group of the instrumented one $\%VA_{it}$ - instrument	576	-15.7692	4.5762	20.2369	5.2909
DNPROD	the percentage rate of growth of labor productivity in a specific sector $\%(VA_{it}/N_{it})$	576	-17.4477	5.0849	76.1210	6.6726
DNPROD – model B instrument	the percentage rate of growth of labor productivity in all sectors within the same technological group of the instrumented one $\%(VA_{it}/N_{it})$ - instrument	576	-11.2659	5.1122	25.8610	5.1308
DPBADL	the percentage rate of growth of bad loans to a specific sector % BADL	576	-99.8833	194.1924	100747.5	4200.567
DPBADL – model B Instrument	the percentage rate of growth of bad loans to all sectors within the same technological group of the instrumented one % BADL - instrument	576	-50.1740	8.6233	93.1388	19.2643
CAPASSRAT	the banking system's capital/asset ratio CAP_t / ASS_t	544	0.0729	0.1048	0.1394	0.0173
DCAPASSRAT	the change of the banking system's capital/asset ratio $\Delta(CAP_t / ASS_t)$	528	-0.0177	0.0018	0.0163	0.0061
DPCAPASSRAT	the percentage rate of growth of the banking system's capital/asset ratio $\%(CAP_t / ASS_t)$	528	-14.7661	2.0159	15.4771	5.6253
DR	Discount rate	592	0.00	0.0690	0.1865	0.0592
DPINVSEC - table 5, model 1 and 1-B	The percentage rate of growth of gross fixed capital formation in each sector $\%INVSEC_{it}$	576	-39.3510	5.4127	60.4620	12.3512
DINVSEC - table 5, model 2 and 2-B	The change of gross fixed capital formation in each sector $\Delta(INVSEC_{iit})$	576	-11832.2	398.2132	10475.3	1660.197
DLOAN	The change of total loans accruing to a specific sector $\Delta(Loan_{it})$	576	-19557.0	1203.351	21873.00	3692.33
DLOAN Instrument - table 5 model 2-B	The change of total loans accruing to all sectors within the same technological group of the instrumented one $\Delta(Loan_{it})$- instrument	576	-39502.0	4924.212	58695.00	11435.10
DVA	The change of value added in a specific sector	576	-16347.50	1747.399	23190.50	3737.917

	$\Delta(VA_{it})$					
DVA instrument – tab 5 model 1B	The change of value added in all sectors within the same technological group of the instrumented one $\Delta(VA_{it})$ - instrument	576	-31061.00	7164.24	39549.00	10441.12
DPCAPSEC table 6, model 1	The percentage rate of growth of stock of non financial assets in each sector $\%CAPSEC_{it}$	576	-3.3676	5.7359	23.9144	4.7806
DPCAPSEC – Instrument - table 6, model 1-B	The percentage rate of growth of stock of non financial assets in all sectors within the same technological group of the instrumented one $\%CAPSEC_{it}$ - instrument	576	-1.7388	5.8467	20.8080	4.3839
DPN - table 6 model 1	The percentage rate of growth of employees in a specific sector $\%N_{it}$	576	-9.7222	-0.2545	10.9080	2.8614
DPN - instrument - table 6 model 1-B	The percentage rate of growth of employees in all sectors within the same technological group of the instrumented one $\%N_{it}$ - instrument	576	-6.5094	-0.4992	4.7990	2.0802

Table 3. Analysis of the allocation of loans accruing to a specific sector

	Dependent Variable: DLSH. Sample: Model 1, 1B, 2, 2B 1981-2017; Model 3, 3B 1984-2017. Panel Least Squares. B= models with instruments					
Regressors	Model 1	Model 1-B	Model 2	Model 2-B	Model 3	Model 3-B
DVARAT	0.8027*** 4.4826	0.8691*** 4.5592	–	–	–	–
DNPRODRAT	–	–	0.0050 0.7477	-0.0250 -0.8919	0.0084 1.1704	-0.0123 -0.5697
DBADLRAT	0.0494 1.5131	-0.0847** -2.3189	0.0495 1.4906	-0.0789** -2.1225	0.0457 1.3884	0.0207 0.5628
DCAPASSRAT	–	–	–	–	0.0019 0.0662	0.0081 0.2774
RGG	–	–	–	–	-3.41E-05 -0.3096	-1.76E-05 -0.1588
INFL	3.99E-19 3.02E-15	5.88E-05 0.4440	-4.67E-05 -0.3210	5.43E-06 0.0401	-3.49E-05 -0.3007	4.88E-06 0.0422
TEC1	-0.0013 -1.3270	–	-0.0024** -2.3389	–	-0.0059*** -4.1204	–
TEC2	-0.0021** -2.4065	–	-0.0027*** -3.1419	–	-0.0071*** -5.8579	–
TEC3	-0.0019* -1.9564	–	-0.0027*** -2.6661	–	-0.0045*** -3.2275	–
TEC4	-0.0027*** -3.085	–	-0.0034*** -3.8952	–	-0.0054*** -4.3734	–
TEC5	-0.0021 -1.6169	–	-0.0027** -2.0711	–	-0.0047*** -2.6107	–
TEC1&2	–	-0.0022*** -2.6981	–	-0.0028*** -3.6229	–	-0.0065*** -6.2141
TEC3&4&5	–	-0.0030*** -3.8494	–	-0.0034*** -4.6655	–	-0.0052*** -5.0953
CRISIS1	4.24E-18 3.70E-15	-0.0002 -0.1553	0.0006 0.3634	-0.0003 -0.2272	–	–
BOOM	2.43E-18 2.18E-15	0.0003 0.3071	-0.0001 -0.1167	3.44E-06 0.0030	–	–
CRISIS2	2.75E-18 2.27E-15	0.0004 0.3374	0.0001 0.0954	7.54E-05 0.0604	–	–
CRISIS1*DVARAT	-1.0522** -2.3431	-1.2565*** -2.6300	–	–	–	–
BOOM*DVARAT	-0.1077 -0.3409	-1.4182*** -4.0602	–	–	–	–
CRISIS2*DVARAT	-0.7377** -2.3688	-0.7490** -2.4749	–	–	–	–
CRISIS1*DNPRODRAT	–	–	-0.0087 -0.5203	0.0544 0.6763	–	–
BOOM*DNPRODRAT	–	–	0.0092 0.7724	0.0207 0.4238	–	–
CRISIS2*DNPRODRAT	–	–	-0.0018 -0.1896	0.0333 0.9625	–	–
LIB	–	–	–	–	-0.0028** 2.5304	-0.0030*** -3.2438
LIB*DNPRODRAT	–	–	–	–	-0.0043 -0.5591	0.0183 0.7348
LIB*DBADLRAT	–	–	–	–	-0.0280 -0.6661	-0.0709 -1.5265
LIB*TEC1	–	–	–	–	0.0056*** 3.5145	–
LIB*TEC2	–	–	–	–	0.0059*** 4.4295	–
LIB*TEC3	–	–	–	–	0.0027* 1.7897	–
LIB*TEC4	–	–	–	–	0.0041*** 2.9989	–
LIB*TEC5	–	–	–	–	0.0036* 1.7852	–
LIB*TEC1&2	–	–	–	–	–	0.0056*** 4.7729
LIB*TEC3&4&5	–	–	–	–	–	0.0035*** 3.1216
CONSTANT	0.0014 1.0677	0.0014 0.9960	0.0018 1.3371	0.0021 1.5062	0.0036*** 3.0007	0.0039*** 3.7602
Adjusted R^2	0.0620	0.0693	0.0216	0.0264	0.08155	0.0808
F Test	3.7148***	4.8896***	1.9072**	2.4198***	3.5997***	4.8599***
No. Observations	576	576	576	576	528	528
Year/sector Fixed Effects	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO

Table 4. Analysis of the rate of growth in total loans accruing to a specific sector

	Dependent Variable: DPLOAN. Sample: Model 4, 4-B, 5, 5-B, 6, 6-b 1984-2017; Model 7, 7-b 1982 2017. Panel Least Squares. B= model with instruments							
Regressors	Model 4	Model 4-B	Model 5	Model 5-B	Model 6	Model 6-B	Model 7	Model 7-B
DPVA	0.5895*** 3.1603	1.0623*** 3.3935	-0.4005* -1.7283	0.5339 1.6359	-0.4932** -2.1557	0.2803 0.8530	–	–
DNPROD	-0.5201** -2.4885	-0.8704** -2.5234	–	–	–	–	-0.2120 -0.9326	-0.1755 -0.5311
DPBADL	-5.07E-05 -0.4614	-0.0909*** -3.0251	-8.66E-05 -0.7895	-0.1333*** -4.1315	-7.05E-05 -0.6527	-0.1442*** -4.5159	-0.0055** -2.0648	0.0084 0.0847
DPCAPASSRAT	0.1247 1.4563	0.1889** 2.1723	0.1331 1.5032	0.2230** 2.4335	0.1322 1.5210	0.2312** 2.5580	–	–
CAPASSRAT	–	–	–	–	–	–	-225.664*** -3.6427	-227.603*** -3.4555
RGG	–	–	–	–	–	–	1.6192*** 5.0891	1.6934*** 4.1603
INFL	2.5651*** 7.9075	2.7718*** 8.1886	1.7283*** 3.4702	1.8509*** 3.7517	1.7705*** 3.6207	1.9930*** 4.0845	1.3970*** 3.1363	1.5156*** 2.9678
DR	–	–	–	–	–	–	2.5662*** 5.1697	2.6935*** 5.1687
TEC1	2.2143 1.3062	–	–	–	0.6847 0.4333	–	-7.5440** -2.2326	–
TEC2	-3.5415** -2.4957	–	–	–	-4.2305*** -3.0528	–	-10.743*** -3.7612	–
TEC3	-3.2862* -1.9618	–	–	–	-4.6047*** -2.8779	–	-5.6925* -1.7286	–
TEC4	-3.5889** -2.5075	–	–	–	-4.8691*** -3.5108	–	-9.0294*** -3.1461	–
TEC5	-3.1440 -1.4820	–	–	–	-4.0962** -1.9889	–	-5.9714 -1.3903	–
TEC1&2	–	-0.4818 -0.3546	–	–	–	-2.1031* -1.7449	–	-10.034*** -3.9894
TEC3&4&5	–	-2.9054** -2.1628	–	–	–	-4.7538*** -4.0251	–	-7.6006*** -3.0283
CRISIS1	–	–	0.1693 0.0542	3.7332 0.9360	-0.5334 -0.1737	2.2860 0.5788	–	–
BOOM	–	–	-0.9688 -0.3077	5.5462 1.5063	-1.2475 -0.4030	4.7040 1.2935	–	–
CRISIS2	–	–	-6.0111* -1.7859	3.5268 0.9112	-6.6526** -2.0106	2.0442 0.5329	–	–
CRISIS1*DPVA	–	–	0.6962* 1.9243	1.2250** 2.3639	0.7726** 2.1702	1.3958*** 2.7221	–	–
BOOM*DPVA	–	–	0.6902** 2.1918	-0.1009 -0.2157	0.6425** 2.0614	-0.2116 -0.4570	–	–
CRISIS2*DPVA	–	–	0.7392*** 2.6662	-0.4842 -1.2420	0.8518*** 3.1071	-0.2352 -0.6036	–	–
LIB	5.6363*** 3.2003	6.8422*** 3.8811	–	–	–	–	2.8905 0.9710	4.7870 1.3289
LIB*DNPROD	–	–	–	–	–	–	0.0945 0.3830	-0.1493 -0.4136
LIB*DPBADL	–	–	–	–	–	–	0.0055** 2.0322	-0.0261 -0.2529
LIB*TEC1	–	–	–	–	–	–	12.0208*** 3.1879	–
LIB*TEC2	–	–	–	–	–	–	8.3007*** 2.5878	–
LIB*TEC3	–	–	–	–	–	–	1.4602 0.3957	–
LIB*TEC4	–	–	–	–	–	–	5.8923* 1.8310	–
LIB*TEC5	–	–	–	–	–	–	2.7441 0.5696	–
LIB*TEC1&2	–	–	–	–	–	–	–	10.2710*** 3.6411
LIB*TEC3&4&5	–	–	–	–	–	–	–	4.1704 1.4889
CONSTANT	-4.8341** -1.9683	-6.5709*** -2.6180	3.4147 0.8871	-4.5834 -1.0918	6.4263* 1.6627	-0.7488 -0.1751	26.0452*** 3.3589	24.7964*** 3.0143
Adjusted R^2	0.1719	0.2130	0.1767	0.2246	0.2068	0.2459	0.3320	0.3177
F Test	10.9457***	18.8329***	12.3094***	16.2662***	10.1597***	15.3241***	15.2062***	20.4453***
No. Observations	528	528	528	528	528	528	544	544
Year/sector Fixed Effects	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO

Table 5. Determinants of investments

	Sample 1982-2017. Panel Least Squares. B=models with instruments			
	Dependent Variable: DPINVSEC		Dependent Variable: DINVSEC	
Regressor	Model 1	Model 1-B	Model 2	Model 2-B
DPVA (-1)	0.3064*** 4.1525	0.5362*** 4.9682	-	-
DPLOAN (-1)	0.0252 0.8040	-0.1164** -2.0450	-	-
DVA (-1)	-	-	0.1817*** 8.7305	0.0403*** 4.7496
DLOAN (-1)	-	-	-0.0281 -1.2674	-0.0129 -1.5797
Constant	3.5926*** 5.5938	3.6297*** 5.2353	115.4763 1.5813	177.1383** 2.1035
Adjusted R^2	0.0318	0.0392	0.1414	0.0410
F Test	10.1698***	12.4038***	47.0134***	12.9433***
No. Observations	560	560	560	560

Table 6. Production function and Solow residual calculation

	Dependent Variable: DPVA. Sample 1981-2017. Panel Least Squares. B=model with instruments	
Regressor	Model 1	Model 1-B
DPCAPSEC	0.8749*** 30.9298	0.8944*** 28.1652
DPN	0.7111*** 9.6670	0.3190*** 2.9396
Adjusted R^2	0.4775	0.3836
Log likelihood	-1751.03	-1799.116
No. Observations	576	576

Table 7. Determinants of Solow residual

	Sample 1981-2017. Panel Least Squares. B=model with instruments	
Regressor	Model 1 Dependent Variable: Residual Model 1 table 6	Model 1-B Dependent Variable: Residual Model 1-B table 6
DPLOAN	-0.0360*** -2.6764	-0.0816*** -3.0555
INFL	0.1267** 2.1448	0.1484** 2.2627
RGG	0.5620*** 4.7956	0.9251*** 6.9155
TEC 1	1.9412*** 2.8373	-
TEC 2	0.6768 1.1249	-
TEC 3	1.3198* 1.9232	-
TEC 4	0.5878 0.9736	-
TEC 5	-0.7408 -0.8236	-
TEC 1&2	-	0.4186 0.7415
TEC 3&4&5	-	-0.3062 -0.5521
CONSTANT	-1.5472*** -3.5027	-1.4396*** -2.9740
Adjusted R^2	0.0610	0.0845
F Test	5.6679***	11.6177***
No. Observations	576	576

Table 8. Financial dependence and banking support to the Italian branches

	(A)	(B)							
	rank Tech c	rank Ext d	Tech cont	Ext dep	rank 81-90	rank 91-00	rank 01-10	rank 11-17	rank med
3511 Basic exclud fert, 352 Other chemicals, 3522 Drugs	2	1	4	0.653	6	5	6	6	6
322 Apparel, 3211 Spinning, 3825 Office, computing, 383 Elect. Machinery	1	2	5	0.562	9	9	9	8	9
355 Rubber products, 356 Plastic products, 3513 Synthetic resins	7	3	2	0.510	7	7	7	7	7
382 Machinery	2	4	4	0.450	3	3	4	4	4
384 Transp. Eq, 3841 Ship, 3843 Motor veichle	2	5	4	0.387	5	8	8	9	8
341 Paper and products, 3411 Pulp, paper, 342 Printing & publishing	5	6	3	0.177	8	6	5	5	6
361 Pottery, 362 Glass, 369 Non metal products, 371 Iron and steel	7	7	2	0.130	2	2	2	1	2
323 Leather, 324 Footwear, 321 Textile	5	8	3	0.060	1	1	1	2	1
311 Food products, 313 Beverages, 314 Tobacco	7	9	2	-0.077	4	4	3	3	4
Correlation with (A)					-0.312	-0.422	-0.569	-0.587	-0.493
Correlation with (B)					-0.617	-0.583	-0.750	-0.683	-0.688
Correlation A & B		0.642							

Appendix A Granger causality tests

a) RGG Granger causes DPLOAN

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
RGG does not Granger Cause DPLOAN	576	21.8070	7.E-10
DPLOAN does not Granger Cause RGG		1.64280	0.1944

b) DBADLRAT and DLSH cause each the other (Granger feedback effect)

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DBADLRAT does not Granger Cause DLSH	576	6.22853	0.0021
DLSH does not Granger Cause DBADLRAT		5.76508	0.0033

c) DVARAT and DLSH cause each the other (Granger feedback effect)

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DVARAT does not Granger Cause DLSH	570	33.5383	2.E-14
DLSH does not Granger Cause DVARAT		4.59058	0.0105

d) No Granger causality link between DPBADL and DPLOAN

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DPBADL does not Granger Cause DPLOAN	576	0.10818	0.8975
DPLOAN does not Granger Cause DPBADL		0.02208	0.9782

e) DPVA and DPLOAN cause each the other (Granger feedback effect)

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DPVA does not Granger Cause DPLOAN	570	30.4528	3.E-13
DPLOAN does not Granger Cause DPVA		2.41305	0.0905

f) No Granger causality link between DPVA and DNPROD

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DPVA does not Granger Cause DNPROD	570	0.95507	0.3854
DNPROD does not Granger Cause DPVA		1.33632	0.2636

g1) DPLOAN and DNPROD cause each the other (Granger feedback effect)

Sample: 1981 2019
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
DPLOAN does not Granger Cause DNPROD	586	3.69121	0.0552
DNPROD does not Granger Cause DPLOAN		7.38372	0.0068

g2) DNPROD Granger causes DPLOAN

Sample: 1981 2019
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DNPROD does not Granger Cause DPLOAN	570	20.1091	4.E-09
DPLOAN does not Granger Cause DNPROD		1.17043	0.3110

g3) No Granger causality link between DNPROD and DPLOAN

Sample: 1981 2019
Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
DNPROD does not Granger Cause DPLOAN	554	1.58283	0.1925
DPLOAN does not Granger Cause DNPROD		0.96489	0.4090

g4) DNPROD and DPLOAN cause each the other (Granger feedback effect)

Sample: 1981 2019
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DNPROD does not Granger Cause DPLOAN	538	3.54977	0.0072
DPLOAN does not Granger Cause DNPROD		1.99457	0.0940