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Impact of Credit Market Development and Stability on Productivity: New Evidence from the Industry Level.*

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Using data on manufacturing industries (aggregated at the 2-digit level) from 118 advanced and developing countries, covering the period 1980-2014, I reassess the impact of financial development and provide new evidence on the effect of the volatility of credit on the growth of labor productivity. I show that labor productivity is boosted by the amount of credit and hindered by the variability of credit, but only in Pavitt's (1984) category of supplier-dominated industries. The amount and variability of credit seem to have no bearing on the growth of labor productivity in groups of science-based, specialized suppliers and scale-intensive sectors.

Key Words: Financial development; Credit variability; Labor productivity.
JEL Classification Numbers: E44, G21, J24.

1. INTRODUCTION

Labor productivity growth is crucial in order to increase living standards. The aim of this paper is to reassess the extent to which financial development boosts labor productivity in manufacturing industries. Domestic credit to the private sector — the most popular measure of the depth of financial markets — doubled at the world aggregate level from around 70 percent of GDP in 1970 to 140 percent in 1999. The growth of credit in the last 16 years was negative in two periods, i.e. 2000-2002 and 2007-2010; the subsequent recovery increased the credit-to-GDP ratio to only 126 percent in 2015. These years were also marked by high variability of credit evidenced by an increase in the standard deviation of the annual change in the credit-to-GDP ratio from 3.4 in the 1980s and 3.2 in the 1990s to 4.4 in 2000-2015.

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An important contribution of this paper is a joint analysis of the impact of the level and variability of credit to the private sector on labor productivity in a sample covering 118 advanced, emerging and developing countries. The literature on the finance-growth nexus is abundant. However, it is devoted to the impact of credit availability on productivity, while the relationship between the latter and the variability of credit supply has not been examined. I show that regression models used to study the influence of financial development on productivity suffer from the omitted variable bias if a measure of credit variability is not included in the set of covariates.

A focus on the heterogeneity of sectors is another advantage of this paper over other studies of the relationship between financial development and productivity at the sectoral level. Persistent productivity differentials can be explained, inter alia, by differences in sources and patterns of innovation, size of firms and market structure. These characteristics are likely to affect the magnitude and sign of the effects of the level and variability of credit on labor productivity. It is therefore justified to compare the influence of finance on productivity growth in groups of sectors which are similar in terms of technological change, production systems and the market environment in which firms operate.

In this paper the diversity of manufacturing industries is boiled down to the four classes defined in Pavitt's Taxonomy (Pavitt, 1984). Scale-intensive industries rely on learning-by-doing to achieve more efficient production process. Firms in supplier-dominated sectors are dependent on external sources of innovation. Specialized suppliers are small firms producing machinery and equipment for other firms. Large investments in R&D, cooperation with universities and research institutes are the characteristics of science-based industries.

The role of finance in productivity growth turned out to depend on whether firms in an industry are science-based, scale-intensive, specialized suppliers, or supplier-dominated. Using the indexes of dependence on external finance to alleviate the problem of the endogeneity of financial development, I show that the impact of the amount of credit on labor productivity is not uniformly positive across the four groups of sectors. The same is true of credit variability, which seems to have a distinct and negative effect on the growth of value added per employee.

The hypotheses regarding the signs of the effects that the amount and variability of credit have on labor productivity are presented in section 3, and section 2 is devoted to a review of the literature on the finance—productivity nexus. Data and methodology are described in section 4 and the empirical results are discussed in section 5. Section 6 contains a conclusive summary.

2. FINANCE AND PRODUCTIVITY GROWTH

Sectoral labor productivity, defined in this paper as value added per employee, corresponds to GDP per capita, which is used as the dependent variable in the analyses of the relationship between growth and financial development at the level of national economies. The results of these studies will be briefly reviewed before attention turns to the literature on finance and growth of industries.

According to Levine (1997) financial development spurs economic growth because financial institutions help allocate resources efficiently, monitor borrowers effectively, mobilize savings and promote specialization (through facilitating the exchange of goods) and ease the trading, hedging, and pooling of risk. Early research confirmed the positive influence of financial development on growth in general (e.g. Wu, Hou, and Cheng 2010) and, in particular, through increasing the level and efficiency of capital accumulation (King and Levine, 1993), improving productivity (Beck, Levine, and Loayza, 2000; Nourzad, 2002; Han and Shen, 2015; Madsen and Ang, 2016) accelerating technology catch-up (Aghion, Howitt, and Mayer-Foulkes, 2005), or through its contribution to both investment and total factor productivity growth (Benhabib and Spiegel, 2000).

More recently, the "too much finance" hypothesis, which suggests that there might be limits to the benefits of financial development, has been put forward and has found support in empirical research. Arcand, Berkes, and Panizza (2015) showed that the marginal effect of financial depth on output growth becomes negative when credit to the private sector reaches 80-100% of GDP. The threshold values estimated by Law and Singh (2014) and Cournède and Denk (2015) were equal to 88% and 100% of GDP respectively. Other examples of empirical research that indicates a non-linear relationship between finance and growth include Deidda and Fattouh (2002), Rioja and Valev (2004), Shen and Lee (2006), Huang and Lin (2009), Jude (2010), Cecchetti and Kharroubi (2012), Samargandi, Fidrmuc, and Ghosh (2015) and Fagerberg and Srholec (2016).

Research on the impact of financial development on growth at the sectoral level was given impetus by Rajan and Zingales (1998), who constructed the index of dependence of sectors on external financing to cope with the problem of endogeneity, namely reverse causation, in regressions with growth and financial development as dependent and explanatory variables, respectively. They confirmed that more domestic credit to the private sector stimulates the growth of value added in sectors that are more dependent on external financing. The results proved to be robust to the inclusion of other financial variables as covariates, such as financial integration (Guiso, Jappelli, Padula, and Pagano, 2004) or financial innovation (Beck, Chen, Lin, and Song, 2016), both of which were found to also boost growth. These findings were revised and extended by Inklaar and Koetter (2008), who demonstrated that while the amount of credit is an important determinant of the growth of value added, efficiency of banks (in particular profit efficiency) was more important for the growth of labor productivity.

There is also evidence at the sectoral level that financial markets that are too large slow the growth of financially dependent industries (Manganelli and Popov, 2013). Aizenman, Jinjarak, and Park (2015) failed to validate the non-linear impact on growth of credit to the private sector and indicated an inverted U-shaped relationship between growth and quality of finance measured by the ratio of credit to value added in the financial and business services sector.

Fisman and Love (2005, 2007) distinguished between short- and long-term allocative effects of financial development. They showed that more financially developed countries specialized in the long-run in financially dependent industries, i.e. sectors that were more dependent on external finance, had a larger share of total production. In the short-run, financial development accelerated the expansion of sectors with high growth potential, regardless of their dependence on external financing. Investment also increased more in growing than in declining industries in countries with more developed financial markets (Wurgler, 2000).

Rioja, Rios-Avila, and Valev (2017) found that recessions have a negative effect on labor productivity in all sectors, but industries more dependent on external financing suffer more from recessions accompanied by banking crises. Moreover, the negative effect of aggregate uncertainty on productivity growth during recession is particularly strong in industries that depend heavily on external finance (Choi, Furceri, Huang, and Loungani, 2018). The impact of financial shocks (defined as increases in the costs of funds) on productivity was found to be negative and economically meaningful in U.S. and Canadian industries (Estevão and Severo, 2011).

The effects of financial shocks have recently also been investigated at the firm level (e.g. Chodorow-Reich, 2014; Cingano, 2016; Dörr, Raissi, and Weber, 2017; Manaresi and Pierri, 2018). A negative effect of banking crises on labor productivity and TFP was also discovered at the country level by Oulton and Sebastiá-Barriel (2016). There are also studies which documented the persistent, depressing effect of the global financial crisis of 2007?2009 on productivity (e.g. Duval, Hong, and Timmer, 2017; Redmond and Van Zandweghe, 2016), but the impact of credit market instability which does not culminate in a crisis has not yet been examined.

There is no comprehensive analysis of the relationship between the amount and variability of credit at the sectoral level, therefore this article is intended to fill this gap in the literature. The use of data aggregated at the industry level made it possible to include in the sample all manufacturing firms from over 100 countries and to study a period of 35 years (1980-

2014). Moreover, methods for measuring volatility at the aggregate level have been established, but similar techniques cannot be applied at the firm level.

3. PAVITT'S TAXONOMY AND THE FINANCE-GROWTH NEXUS

Pavitt (1984) acknowledged differences in technological change across sectors in terms of the sources, nature and impact of innovations. He attributed them to differences in the sources of knowledge inputs (generated from within or without the sector), in the relative importance of intramural and extramural knowledge sources, in whether technological change takes the form of product or process innovations, and in the size and principal activity of innovating firms. He defined 4 categories of sectors.

Firms in science-based (SB) sectors invest heavily in R&D and produce a large proportion of their process and product innovation, therefore they have a high propensity to patent. They are big because dynamic learning economies in production pose a barrier to the entry of imitators.

Large size is also a characteristic of firms in scale-intensive (SI) industries which exploit economies of scale. Technological progress in these sectors takes the form of process innovation and consists in the ability to design and operate large-scale continuous processes and assembly systems. The secrecy around innovation processes is maintained under patent protection. In-house R&D is the main source of innovation in science-based and scale-intensive industries.

By contrast, firms in traditional sectors, referred to as supplier-dominated (SD), introduce technological change through the equipment and materials provided by other industries, i.e. they make a minor contribution to their process innovation. They are usually small and do not carry out in-house R&D or engineering activities. They appropriate knowledge in non-technical forms, such as trademarks, advertising and design.

The category of specialized suppliers (SS) includes industries that produce machinery and equipment. Their competitive advantage is based on improvements in product design and their innovative activities are therefore focused on product innovations. Innovating firms are relatively small and rely on customers and other firms outside the sector to be major contributors to innovations. Although R&D is present in these sectors, tacit knowledge and experience embodied in the labor force are an essential innovative input.

The Pavitt's classification has been used in previous research on innovation (e.g. Hitchen, Nylund, and Viardot 2017; Ryu and Lee, 2016; Forsman, 2011; De Jong and Marsili, 2006). Labor market outcomes also seem to vary across Pavitt's categories (for an analysis of growth of employment after the global financial crisis, see Sedita, De Noni, and Pilotti, 2017; for an analysis of the relationship between the creation and loss of jobs and technological change, see Bogliacino and Pianta, 2010). It is important to note that Pavitt's taxonomy was also considered in the literature as a determinant of firms' access to credit. Cenni, Monferrà, Salotti, Sangiorgi, and Torluccio (2015) studied credit rationing and relationship lending for different Pavitt's classes and firm size groups. Marotta (2005) and Agostino and Trivieri (2014) considered Pavitt's classification as a determinant of trade credit and bank debt, respectively. Dummies for Pavitt's sectors were included by Cosci, Guida, and Meliciani (forthcoming) as the determinants of financial constraints.

This brief summary of the defining features of Pavitt's classes led to the hypothesis regarding the impact of the amount and variability of credit on labor productivity. Credit market imperfections in general and a limited and intermittent access to the market in particular increase the costs of accumulation of physical capital. A high level of financial development should have the strongest positive influence on labor productivity in sectors which rely on physical capital accumulation as a source of innovation.

In contrast to a profusion of loans, variability in the amount of credit induces uncertainty and reduces the attractiveness of external financing from banks. High volatility of credit supply should have a detrimental effect on productivity in sectors in which firms are small and innovation is inherent in physical capital accumulation. Bank overdrafts and bank loans are the two key sources of external financing that are used or considered relevant for small and medium enterprises (see e.g. European Central Bank, 2018).

These arguments led to the main hypothesis of the paper. The impact of the amount and variability of credit is the most pronounced in supplier-dominated industries. Wider access to credit boosts productivity in these sectors because physical capital accumulation is a vehicle for technological progress therein. Credit variability slows productivity growth in supplier-dominated industries because small firms face binding financial constraints during the contractionary phase of the credit cycle which impinge on physical capital accumulation and the concomitant adoption of innovations.

The corollary that the amount and variability of credit have weak effects on labor productivity in specialized suppliers, scale-intensive, and science-based industries is underpinned by the fact that banks are risk averse and unable to overcome information and agency problems in industries that carry out a lot of R&D activities. In fact, even large established firms which are barely credit constrained prefer internal funds for financing R&D investments and they manage their cash flow to ensure this (Hall and Lerner, 2010; Brown and Petersen, 2011). Hsu, Tian, and Xu (2014) investigated the impact of financial development on several measures of innovative efforts and found that the development of credit markets seems to discourage innovation in industries that are more higih-tech intensive. Pradhan, Arvin, Hall, and Nair (2016) studied short- and long-run relations between domestic credit and the intensity of innovative efforts measured by patents, research personnel and spending. They failed to find Granger causal relationships that were uniform across various periods and innovation measures. It has to be established empirically whether the effects of the amount and variability of credit on labor productivity in other than traditional, supplier-dominated industries are statistically discernible from 0.

4. DATA AND METHODOLOGY

In the empirical research on the impact of financial development on growth, particular attention should be paid to the issue of reverse causality. To deal with this problem, Rajan and Zingales (1998) constructed a measure of manufacturing sectors' dependence on external financing which ensures the exogeneity of proxies for financial development in growth regressions. The following modified version of their estimating equation will be used in this paper:

$$y_{ijt} = \alpha \text{Productivity gap}_{it-1} + \beta(\text{ExtDep} * \text{Fin})_{ijt-1} + \omega_{ij} + \gamma_t + \varepsilon_{ijt} \quad (1)$$

where i stands for manufacturing industry at the 2-digit level of ISIC Revision 2 classification (codes 16-37), j for country, and t indexes periods. To filter out business-cycle variations, all variables were averaged in non-overlapping 5-year periods between 1980 and 2014, i.e. the number of time series observations t in the panel was 7. The regression equation includes dummies for periods, γ, fixed effects for each sector i in country j, ω_{ij}, and idiosyncratic errors, ε_{ijt}.

The dependent variable y is the annual growth rate of labor productivity, i.e. the first difference of the log of real value added divided by the number of employees. To obtain the real value added, I used data reported in local currency and converted it to constant international dollars using the implicit deflator derived from the World Economic Outlook Database compiled by the International Monetary Fund[1]. All data at the sectoral level was retrieved from the Database on Industrial Statistics compiled by the United Nations Industrial Development Organization. Included in the sample are 118 advanced, emerging, and developing countries and the period under study is 1980-2014.

[1]The deflation procedure consisted in multiplying the nominal domestic currency value by the ratio of real GDP per capita in international dollars to real GDP per capita in domestic currency.

Productivity gap was calculated as the percentage difference in labor productivity relative to the country where the sector i was the most productive at the beginning of each 5-year period t, i.e. $\ln\left(\max_j \frac{\text{value added}}{\text{employees}_{ijt}}\right) - \ln\frac{\text{value added}}{\text{employees}_{ijt}}$. This variable is intended to measure the potential for convergence to the world's productivity frontier. Griffith, Redding, and Van Reenen (2003) constructed a similar measure of the distance to the technology frontier in their theoretical and empirical models that explain total factor productivity growth.

The vector ExtDep $*$ Fin contains two variables that capture the characteristics of the financial market (Fin) multiplied by the dependence on external financing (ExtDep). To overcome concerns about the endogeneity of financial variables, their values were lagged by one period. The first characteristic of the credit market is the amount of credit, labeled development. I used the standard measure of credit market depth, i.e. the stock of credit to the private sector in percent of GDP. The data came from the World Bank's World Development Indicators database.

The second characteristic is the volatility of the stock of credit, labelled volatility. To ensure the robustness of results, two proxies for credit volatility were constructed. The procedure applied to obtain the first measure of credit volatility was based on a regression analysis. I regressed the credit-to-GDP ratio on its own lagged value and the time trend. The standard deviation of the residuals was the first proxy for credit volatility. The second measure of volatility was based on the Hodrick-Prescott filter and equaled the standard deviation of the cyclical component of the credit-to-GDP series in each 5-year period. Provided that the duration of the financial cycle is at least twice as long as the business cycle, the trend should be extracted with the lambda parameter equal to 125,000 for quarterly data (Drehmann, Borio, Gambacorta, Jiménez, and Trucharte 2010). Following the Ravn and Uhlig (2002) rule, the value of the lambda parameter for the annual data I used was 488. To improve the precision of measuring volatility and trend components of the credit-to-GDP ratio, both methods were applied to data covering 1960-2016.

All elements of vector Fin presented above were multiplied by the dependence on external financing ExtDep. This measure was borrowed from Klapper, Laeven, and Rajan (2006), who computed the indexes for the years 1980-1989 and 1990-1999[2]. The index of external dependence calculated for the 1990s was used for the entire period 1990-2014.

The specification of the model in (1) assumes that the growth of productivity is not persistent; this contrasts with the results of empirical research, which suggest that it is statistically best estimated as an autoregressive

[2] I thank Luc Laeven for sharing data.

process[3]. Therefore, the main specification used in this paper included the lagged value of the dependent variable as one of the regressors. To capture the heterogeneity of the estimated coefficients of the financial variables across Pavitt's groups, four binary variables, D_{pi}, were interacted with the financial variables. These dummies corresponded to the 4 groups of industries defined in Pavitt's Taxonomy; for each industry only the respective dummy was coded 1 and the remaining took the value of 0. The amended specification of the model took the following form:

$$\begin{aligned} y_{ijt} &= \alpha_1 y_{ijt-1} + \alpha_2 \text{Productivity gap}_{it-1} + \sum_{p=1}^{4} \beta_p D_{pi} (\text{ExtDep} * \text{Fin})_{ijt-1} \\ &\quad + \omega_{ij} + \gamma_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

The regression equation (2) was a dynamic panel data model in which the number of time series observations was 7. Three different techniques were applied to deal with the "small T" bias, i.e. to solve the problem arising from a correlation between the lagged dependent variable and the error which arises when a dynamic panel data model is estimated by the fixed effects estimator.

To remove the "small T" bias, the bootstrap-corrected fixed-effects (BCFE) estimator of Everaert and Pozzi (2007) uses a bootstrap-based numerical method to obtain the value of the bias instead of analytical approximations based on a strict set of assumptions which are often violated in practice. I used the algorithm proposed by De Vos, Everaert, and Ruyssen (2015) for unbalanced panels and generated bootstrap samples under the assumption that the error terms were from the normal distribution with cross-section-specific variance[4].

Quasi-maximum likelihood (QML) estimation was the second strategy used to cope with the bias that is peculiar to dynamic panel data covering short time periods. Unlike the BCFE procedure, the QML approach does not consist in estimating and removing the bias; instead, it is designed to avoid it by modelling the unconditional likelihood function. The maximum likelihood estimation procedure of Kripfganz (2016) employs the representation proposed by Hsiao, Pesaran, and Tahmiscioglu (2002) for the initial observations of the dynamic model in first differences[5]. The initial observations were estimated using all the time-varying right-hand-side variables

[3]Everaert and De Simone (2007) estimated the autoregressive coefficient in TFP growth regression to be equal to 0.95.

[4]Under the assumption of cross-sectional heteroscedasticity, the error term was resampled over time within cross-sections.

[5]The first-difference transformation reduced the number of observations reported in the next section.

in the model and as many forward-looking periods as were available for the shortest panel.

To deal with the "small T" and endogeneity problems, I also used the System Generalized Method of Moments (GMM) of Arellano and Bover (1995) and Blundell and Bond (1991), which relies on the instrumental variables technique. This estimator suffers from poor small-sample properties, finite sample bias due to the weak instrument problem, and sensitivity of results to the number and choice of instruments. Despite its flaws, it has been very popular in applied work; therefore, it will be used in this paper alongside the BCFE and QML estimators, which are underrepresented in empirical work.

5. RESULTS

This paper claims that there is need to acknowledge that financial development exerts a diverse influence on the growth of labor productivity in Pavitt's categories. Ignoring this heterogeneity — as other studies of the finance-growth nexus at the sectoral level used to — can produce misleading results. To illustrate this point, I present in Table 1 and Table 2 the estimation results of the baseline model that imposes equality of the coefficients on financial development across sectors. The static panel data model specified in equation (1) was estimated by using the fixed effects ordinary least squares (OLS) estimator. The Hausman test indicated that fixed effects were preferred over random effects.

TABLE 1.
Labor Productivity-Finance Nexus under the Assumption of Homogeneity; OLS Estimates

Volatility measure	Regression residuals	Hodrick-Prescott filter
Productivity gap	0.106^{***}	0.108^{***}
	(0.009)	(0.009)
Development	0.002^{**}	0.002
	(0.001)	(0.001)
Volatility	-0.030^{***}	-0.027^{***}
	(0.005)	(0.006)
Observations	7,310	7,358
Hausman test χ^2 (p-value)	169.66 (0.0)	178.37 (0.0)

Robust standard errors are shown in brackets; stars indicate significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables were averaged over 5-year periods. Dummies for each 5-year period were included. The Development and Volatility variables were multiplied in each sector by the corresponding index of dependence on external financing.

Besides the evidence that distance to the frontier stimulates productivity growth, two key insights can be gained from Table 1. First, volatility of credit had a highly significant negative influence on the rate of growth of labor productivity in manufacturing in 1980-2014. Second, the statistical significance of the positive impact of financial development on productivity growth depended on the measure of the volatility of credit included in the model. The coefficient on the credit-to-GDP ratio was not significant if the variability of credit was measured by the standard deviation of the cyclical component obtained from Hodrick-Prescott filtering. The reliability of these results can be questioned because the lagged value of labor productivity was omitted from the set of covariates. Inclusion of this variable made it possible to control in the regression for the contemporaneous impact of time-invariant factors which affected the lagged value of labor productivity. The estimation results of the baseline dynamic panel data models are shown in Table 2.

TABLE 2.

Labor Productivity-Finance Nexus under the Assumption of Homogeneity; Dynamic Panel Estimates

Volatility measure	Regression residuals			Hodrick-Prescott filter		
Estimation method	BCFE	QML	GMM	BCFE	QML	GMM
Lagged productivity	0.222^{***}	0.120^{***}	0.083^{***}	0.227^{***}	0.132^{***}	0.082^{**}
	(0.031)	(0.034)	(0.032)	(0.030)	(0.034)	(0.033)
Productivity gap	0.106^{***}	0.097^{***}	0.036^{**}	0.106^{***}	0.094^{***}	0.039^{**}
	(0.008)	(0.011)	(0.016)	(0.012)	(0.010)	(0.016)
Development	0.003^{*}	0.002	0.004^{***}	0.002^{*}	0.002	0.005^{***}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	-0.023^{***}	-0.020^{***}	-0.037^{***}	-0.016^{***}	-0.018^{**}	-0.050^{***}
	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.011)
Observations	5,239	4,373	5,594	5,254	4,406	5,611

Robust standard errors are shown in brackets; stars indicate significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables were averaged over 5-year periods. Dummies for each 5-year period were included. The Development and Volatility variables were multiplied in each sector by the corresponding index of dependence on external financing. Hansen J statistic: 23.74 ($p = 0.164$) in (3), 18.15 ($p = 0.255$) in (6).

Table 2 confirms that the growth of labor productivity is an autoregressive process because the coefficient on the lagged value of the rate of growth of labor productivity is statistically significant. The results strengthen the conclusion that the volatility of the amount of credit was a drag on productivity growth. The positive impact of financial development remains unsubstantiated because its significance depended on the estimation method and was zero when the QML estimator was applied. The insignificance of credit to the private sector may be due to the fact that the relationship between this variable and labor productivity is non-linear. In fact, the

TABLE 3.

Labor Productivity?Finance Nexus in Pavitt's Groups

Volatility measure	Regression residuals			Hodrick-Prescott filter		
	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	BCFE	QML	GMM	BCFE	QML	GMM
Lagged productivity	0.222^{***}	0.120^{***}	0.103^{***}	0.227^{***}	0.132^{***}	0.100^{***}
	(0.030)	(0.035)	(0.035)	(0.029)	(0.034)	(0.035)
Productivity gap	0.107^{***}	0.097^{***}	0.014^{*}	0.107^{***}	0.095^{***}	0.015^{*}
	(0.008)	(0.011)	(0.008)	(0.012)	(0.010)	(0.008)
Development * SB	0.002	−0.001	0.001	0.002	−0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Development * SS	−0.007	0.000	0.006	−0.002	0.008	0.017
	(0.024)	(0.017)	(0.009)	(0.030)	(0.018)	(0.015)
Development * SI	−0.002	−0.003	−0.000	−0.003	−0.003	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Development * SD	0.004^{*}	0.004^{**}	0.004^{***}	0.003^{*}	0.004^{**}	0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Volatility * SB	−0.008	−0.003	−0.010	−0.008	−0.001	−0.007
	(0.009)	(0.008)	(0.013)	(0.014)	(0.012)	(0.012)
Volatility * SS	0.015	0.017	−0.086	−0.025	−0.055	−0.141
	(0.054)	(0.039)	(0.085)	(0.085)	(0.059)	(0.099)
Volatility * SI	−0.005	0.004	−0.033	−0.001	−0.008	−0.026
	(0.020)	(0.017)	(0.023)	(0.018)	(0.017)	(0.018)
Volatility * SD	-0.039^{***}	-0.029^{***}	-0.066^{***}	-0.022^{**}	-0.022^{**}	-0.059^{***}
	(0.010)	(0.010)	(0.017)	(0.010)	(0.010)	(0.015)
Observations	5,239	4,373	5,594	5,254	4,406	5,611

Robust standard errors are shown in brackets (a small sample correction was applied in (3) and (6)); stars indicate significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables were averaged over 5-year periods. Dummies for each 5-year period were included. The Development and Volatility variables were multiplied in each sector by the corresponding index of dependence on external financing and by dummies corresponding to 4 groups defined in Pavitt's taxonomy (SB: science-based, SS: specialized suppliers, SI: scale-intensive, SD: supplier-dominated). Hansen J statistic: 79.66 ($p = 0.201$) in (3), 78.69 ($p = 0.223$) in (6).

literature review revealed that there is evidence in favor of the 'too much finance' hypothesis. To test the non-linearity of the relationship between financial development and productivity, I added the squared value of credit to the private sector to the set of regressors. The results shown in Table 5 in the appendix unambiguously demonstrate that the non-linearity hypothesis can be rejected. The coefficient of the squared value of the financial development variable is close to 0 and statistically insignificant, regardless of the estimation method used. Therefore, in the remaining estimates I did not include the quadratic term for financial development.

To assess the extent to which the findings obtained so far are uniform across Pavitt's groups, the model specified in equation (2) was fitted by the three methods described in the preceding section.

TABLE 4.
Labor Productivity?Finance Nexus in Pavitt's Groups; Sensitivity of Results to the Length of The Averaging Period

Volatility measure	Regression residuals			Hodrick-Prescott filter		
	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	BCFE	QML	GMM	BCFE	QML	GMM
Lagged productivity	0.377***	0.117**	0.126***	0.377***	0.117**	0.123***
	(0.088)	(0.047)	(0.034)	(0.089)	(0.047)	(0.033)
Productivity gap	0.395***	0.286***	0.026*	0.395***	0.286***	0.027*
	(0.036)	(0.031)	(0.015)	(0.036)	(0.031)	(0.015)
Development * SB	−0.001	0.002	0.001	−0.001	0.002	0.001
	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)
Development * SS	−0.056	−0.033	0.012	−0.048	−0.026	0.014
	(0.059)	(0.030)	(0.013)	(0.052)	(0.028)	(0.013)
Development * SI	−0.000	0.002	0.001	−0.003	−0.000	0.000
	(0.007)	(0.005)	(0.003)	(0.007)	(0.005)	(0.003)
Development * SD	0.010*	0.012***	0.010***	0.009	0.011***	0.010***
	(0.006)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
Volatility * SB	0.007	−0.002	−0.010	0.009	−0.005	−0.003
	(0.026)	(0.017)	(0.030)	(0.034)	(0.022)	(0.032)
Volatility * SS	0.070	0.063	−0.051	0.027	0.032	−0.078
	(0.135)	(0.098)	(0.114)	(0.096)	(0.076)	(0.101)
Volatility * SI	0.015	0.020	−0.006	0.073	0.064	−0.009
	(0.033)	(0.031)	(0.042)	(0.051)	(0.043)	(0.040)
Volatility * SD	−0.072***	−0.052***	−0.060**	−0.062***	−0.042**	−0.059*
	(0.022)	(0.015)	(0.028)	(0.019)	(0.018)	(0.031)
Observations	2,599	2,445	3,374	2,599	2,445	3,374

Notes: Robust standard errors are shown in brackets (a small sample correction was applied in (3) and (6)); stars indicate significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables were averaged over 7-year periods. Dummies for each 7-year period were included. The Development and Volatility variables were multiplied in each sector by the corresponding index of dependence on external financing and by dummies corresponding to 4 groups defined in Pavitt's taxonomy (SB: science-based, SS: specialized suppliers, SI: scale-intensive, SD: supplier-dominated). Hansen J statistic: 24.80 ($p = 0.417$) in (3), 24.81 ($p = 0.416$) in (6).

Estimation results of the dynamic panel data models reveal that the significance of the characteristics of the credit market is confined to supplier-dominated industries. Only in these sectors does the amount and variability of credit exert, respectively, a positive and negative influence on the rate of growth of labor productivity. It should be stressed that the level of significance of credit instability is higher, regardless of the estimation method and the measure of volatility used. The robustness of results was tested further by extending to 7 years the period over which the averages of all variables are calculated. The resulting reduction to 5 of the number of time series observations in the panel made it necessary to stick to the estimation methods designed to deal with the "small T" bias. The results are shown in Table 4.

The estimation results based on the samples of 5-year and 7-year averages are similar, i.e. they are not sensitive to the length of the averaging period. When the volatility was measured by the standard deviation of the cyclical component of the credit-to-GDP ratio and the BCFE estimator was employed, the level of financial development turned out to be insignificant (see column 4). The coefficient on the productivity gap was bigger when estimates were obtained from 7-year averages, meaning that the process of convergence is not rapid enough to have its full effect in a 5-year period. The consistency of estimation results across several estimation methods, measures of credit volatility, and the length of the averaging period allows a few firm conclusions to be drawn.

6. CONCLUSION

The objective of this paper was to scrutinize the impact of the amount and variability of credit on the growth of labor productivity in the groups of industries defined in Pavitt's taxonomy. I argued that credit variability hampers long-term investment planning, thereby worsening growth performance. I verified this prediction using sectoral data on manufacturing at a 2-digit level of aggregation for 118 advanced and developing countries, covering 1980?2014. To address the problem of endogeneity of financial variables, I adopted the popular methodology based on weighting them by indexes of dependence on external finance.

Respectively, I found that the positive and negative effects of the amount and variability of credit are detectable only in supplier-dominated industries. These traditional sectors do not carry out much R&D and introduce technological change through investment in new capital equipment developed in other sectors. Therefore, the growth of labor productivity in specialized suppliers and in science-based and scale-intensive industries, in which technological progress is not merely a by-product of physical capital accumulation, seems to be independent of the characteristics of the credit market.

The main message of this paper is that financial development is as important for the growth of labor productivity as the stability of credit supply; however, the influence of the depth and stability of the credit market is restricted to supplier-dominated industries. The recommendation which emerges from this paper is that policymakers should promote financial development and the least volatile level of lending by banks in countries where the share of traditional manufacturing sectors in the economy is considerable. The majority of services are in supplier-dominated sectors and an interesting question to be answered by future research is whether the growth of labor productivity beyond manufacturing is also dependent on the characteristics of the credit market.

APPENDIX

TABLE 5.

Non-Linearity of The Relationship between Financial Development and Productivity; Dynamic Panel Estimates

Volatility measure	Regression residuals			Hodrick-Prescott filter		
Estimation method	BCFE	QML	GMM	BCFE	QML	GMM
Lagged productivity	0.223^{***}	0.121^{***}	0.087^{***}	0.228^{***}	0.133^{***}	0.079^{**}
	(0.031)	(0.035)	(0.031)	(0.030)	(0.034)	(0.031)
Productivity gap	0.106^{***}	0.098^{***}	0.038^{***}	0.106^{***}	0.095^{***}	0.036^{**}
	(0.008)	(0.011)	(0.014)	(0.012)	(0.010)	(0.015)
Development	0.003	0.006^{*}	0.001	0.003	0.005^{*}	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Development squared	−0.000	−0.000	0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	-0.023^{***}	-0.015^{**}	-0.034^{***}	-0.015^{***}	-0.012^{*}	-0.049^{***}
	(0.006)	(0.006)	(0.010)	(0.006)	(0.007)	(0.011)
Observations	5,239	4,373	5,594	5,254	4,406	5,611

Robust standard errors are shown in brackets; stars indicate significance level: $***\ p < 0.01$, $**\ p < 0.05$, $^{*}\ p < 0.1$. All variables were averaged over 5-year periods. Dummies for each 5-year period were included. The Development, Development squared, and Volatility variables were multiplied in each sector by the corresponding index of dependence on external financing. Hansen J statistic: 31.76 ($p = 0.201$) in (3), 26.67 ($p = 0.270$) in (6).

REFERENCES

Aghion, P., P. Howitt, and D. Mayer-Foulkes, 2005. The Effect of Financial Development on Convergence: Theory and Evidence. *The Quarterly Journal of Economics* **120(1)**, 173-222.

Agostino, M. and F. Trivieri, 2014. Does Trade Credit Play a Signaling Role? Some Evidence from SMEs Microdata. *Small Business Economics* **42(1)**, 131-151.

Aizenman, J., Y. Jinjarak, and D. Park, 2015. Financial Development and Output Growth in Developing Asia and Latin America: A Comparative Sectoral Analysis. NBER Working Paper no. 20917.

Arcand, J-L, E. Berkes, and U. Panizza, 2015. Too Much Finance? *Journal of Economic Growth* **20(2)**, 105-148.

Arellano, M. and O. Bover 1995. Another Look at The Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics* **68(1)**, 29-51.

Arizala, F., E. Cavallo, and A. Galingo, 2009. Financial Development and TFP Growth: Cross-Country and Industry-Level Evidence. Inter-American Development Bank Research Department Working Papers No. 682.

Beck, T., T. Chen, C. Lin, and N. M. Song, 2016. Financial Innovation: The Bright and Dark Sides. *Journal of Banking and Finance* **72**, 28-51.

Beck, T., R. Levine, and N. Loayza, 2000. Finance and the Sources of Growth. *Journal of Financial Economics* **58(1-2)**, 261-300.

Benhabib, J. and M. M. Spiegel, 2000. The Role of Financial Development in Growth and Investment. *Journal of Economic Growth* **5**, 341-360.

Blundell, R. and S. R. Bond, 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* **87(1)**, 115-143.

Bogliacino, F. and M. Pianta, 2010. Innovation and Employment: A Reinvestigation Using Revised Pavitt Classes. *Research Policy* **39(6)**, 799-809.

Brown, J. R. and B. C. Petersen, 2011. Cash Holdings and R&D Smoothing. *Journal of Corporate Finance* **17(3)**, 694-709.

Cecchetti, S. G. and E. Kharroubi, 2012. Reassessing the Impact of Finance on Growth. BIS Working Paper No. 381.

Cenni, S., S. Monferrà, V. Salotti, M. Sangiorgi, and G. Torluccio, 2015. Credit Rationing and Relationship Lending. Does Firm Size Matter? *Journal of Banking & Finance* **53**, 249-265.

Chodorow-Reich, G., 2014. The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008-9 Financial Crisis. *The Quarterly Journal of Economics* **129(1)**, 1-59.

Choi, S., D. Furceri, Y. Huang, and P. Loungani, 2018. Aggregate Uncertainty and Sectoral Productivity Growth: The Role of Credit Constraints. *Journal of International Money and Finance* **88**, 314-330.

Cingano, F., F. Manaresi, and E. Sette, 2016. Does Credit Crunch Investment Down? New Evidence on the Real Effects of the Bank-Lending Channel. *Review of Financial Studies* **29(10)**, 2737-2773.

Cosci, S., R. Guida, and V. Meliciani, forthcoming. Does Trade Credit Help Relieving Financial Constraints? European Financial Management.

Cournède, B. and O. Denk, 2015. Finance and Economic Growth in OECD and G20 Countries. OECD Economics Department Working Papers No. 1223.

De Jong, J. P. J. and O. Marsili, 2006. The Fruit of Innovations: A Taxonomy of Innovative Small Firms. *Research Policy* **35(2)**, 213-229.

De Vos, I., G. Everaert, and I. Ruyssen, 2015. Bootstrap-Based Bias Correction and Inference for Dynamic Panels with Fixed Effects. *Stata Journal* **15(4)**, 986-1018.

Deidda, L. and B. Fattouh, 2002. Non-Linearity Between Finance and Growth. *Economics Letters* **74(3)**, 339-345.

Dörr, S., M. Raissi, and A. Weber, 2017. Credit-Supply Shocks and Firm Productivity in Italy. IMF Working Paper WP/17/67.

Drehmann, M., C. Borio, L. Gambacorta, G. Jiménez, and C. Trucharte, 2010. Countercyclical Capital Buffers: Exploring Options. BIS Working Paper No. 317.

Duval, R., G. H. Hong, and Y. Timmer, 2017. Financial Frictions and the Great Productivity Slowdown. IMF Working Paper WP/17/129.

Estevão, M. and T. Severo, 2011. Shocks, Financial Dependence, and Efficiency: Evidence from U.S. and Canadian Industries. IMF Working Paper WP/11/199.

European Central Bank, 2018. Survey On the Access to Finance of Enterprises in the Euro Area. October 2017 to March 2018. European Central Bank.

Everaert, G. and L. Pozzi, 2007. Bootstrap-Based Bias Correction for Dynamic Panels. *Journal of Economic Dynamics and Control* **31(4)**, 1160-1184.

Everaert, L. and F. N. De Simone, 2007. Improving the Estimation of Total Factor Productivity Growth: Capital Operating Time in Latent Variable Approach. *Empirical Economics* **33(3)**, 449-468.

Fagerberg, J. and M. Srholec, 2016. Global Dynamics, Capabilities and the Crisis. *Journal of Evolutionary Economics* **26(4)**, 765-784.

Fisman, R. and I. Love, 2007. Financial Dependence and Growth Revisited. *Journal of the European Economic Association* **5(2-3)**, 470-479.

Fisman, R. and I. Love, 2005. Financial Development and Intersectoral Allocation: A New Approach. *Journal of Finance* **59(6)**, 2785-2807.

Forsman, H., 2011. Innovation Capacity and Innovation Development in Small Enterprises. A Comparison Between the Manufacturing and Service Sectors. *Research Policy* **40(5)**, 739-750.

Griffith, R., S. Redding, and J. Van Reenen, 2003. R&D and Absorptive Capacity: Theory and Empirical Evidence. *The Scandinavian Journal of Economics* **105(1)**, 99-118.

Guiso, L., T. Jappelli, M. Padula, and M. Pagano, 2004. Financial Market Integration and Economic Growth in the EU. *Economic Policy (October)*, 523-577.

Hall, B. H. and J. Lerner, 2010. Financing R&D and Innovation. In: B. H. Hall, N. Rosenberg (Eds.). Handbook of the Economics of Innovation. Elsevier, Amsterdam, 609-639.

Han, J. and Y. Shen, 2015. Financial Development and Total Factor Productivity Growth: Evidence from China. *Emerging Markets Finance and Trade* **51(sup1)**, S261-S274.

Hitchen, E. L, P. A. Nylund, and E. Viardot, 2017. The Effectiveness of Open Innovation: Do Size and Performance of Open Innovation Groups Matter? *International Journal of Innovation Management* **21(3)**, 1750042.

Hsiao, C., M. H. Pesaran, and A. K. Tahmiscioglu, 2002. Maximum Likelihood Estimation of Fixed Effects Dynamic Panel Data Models Covering Short Time Periods. *Journal of Econometrics* **109(1)**, 107-150.

Hsu, P-H., X. Tian, and Y. Xu, 2014. Financial Development and Innovation: Cross-Country Evidence. *Journal of Financial Economics* **112(1)**, 116-135.

Huang, H.-C. and S.-C. Lin, 2009. Non-Linear Finance-Growth Nexus. *Economics of Transition* **17(3)**, 439-466.

Inklaar, R. and M. Koetter, 2008. Financial Dependence and Industry Growth in Europe: Better Banks and Higher Productivity. Research Memorandum GD-100.

Jude, E. C., 2010. Financial Development and Growth: A Panel Smooth Regression Approach. *Journal of Economic Development* **35(1)**, 15-33.

King, R. G. and R. Levine, 1993. Finance and Growth: Schumpeter Might Be Right. *The Quarterly Journal of Economics* **108(3)**, 717-737.

Klapper, L., L. Laeven, and R. Rajan, 2006. Entry Regulation as a Barrier to Entrepreneurship. *Journal of Financial Economics* **82**, 591-629.

Kripfganz, S., 2016. Quasi-Maximum Likelihood Estimation of Linear Dynamic Short-T Panel-Data Models. *Stata Journal* **16(4)**, 1013-1038.

Law, S. H., W. C. Lee, and N. Singh, 2018. Revisiting the Finance-Innovation Nexus: Evidence from a Non-Linear Approach. *Journal of Innovation & Knowledge* **3**, 143-153.

Levine, R., 1997. Financial Development and Economic Growth: Views and Agenda. *Journal of Economic Literature* **35(2)**, 688-726.

Madsen, J. B. and J. B. Ang, 2016. Finance-Led Growth in The OECD since the Nineteenth Century: How Does Financial Development Transmit to Growth? *Review of Economics and Statistics* **98(3)**, 552-572.

Manaresi, F. and N. Pierri, 2018. Credit Supply and Productivity Growth. BIS Working Paper Series, No. 711.

Manganelli, S. and A. Popov, 2013. Financial Dependence, Global Growth Opportunities, and Growth Revisited. *Economics Letters* **120**, 123-125.

Marotta, G., 2005. When Do Credit Discounts Matter? Evidence from Italian Firm-Level Data. *Applied Economics* **37(4)**, 403-416.

Nourzad, F., 2002. Financial Development and Productive Efficiency: A Panel Study of Developed and Developing Countries. *Journal of Economics and Finance* **26(2)**, 138-149.

Oulton, N. and M. Sebastiá-Barriel, 2016. Effects of Financial Crises on Productivity, Capital and Employment. *The Review of Income and Wealth* **63(s1)**, S90-S112.

Pavitt, K., 1984. Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research Policy* **13**, 343-373.

Pradhan, R. P., M. B. Arvin, J. H. Hall, and M. Nair, 2016. Innovation, Financial Development and Economic Growth in Eurozone Countries. *Applied Economics Letters* **23(16)**, 1141-1144.

Rajan, R. G. and L. Zingales, 1998. Financial Dependence and Growth. *American Economic Review* **88(3)**, 559-586.

Ravn, M. O. and H. Uhlig, 2002. On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *The Review of Economics and Statistics* **84(2)**, 371-376.

Redmond, M. and W. Van Zandweghe, 2016. The Lasting Damage from the Financial Crisis to U.S. Productivity. *Federal Reserve Bank of Kansas City Economic Review (First Quarter)*, 39-64.

Rioja, F. and N. Valev, 2004. Does One Size Fit All?: A Reexamination of the Finance and Growth Relationship. *Journal of Development Economics* **74(2)**, 429-447.

Rioja, F., F. Rios-Avila, and N. Valev, 2017. Productivity during Recessions with Banking Crises: Inter-Industry Evidence. *Economics Letters* **152**, 50-53.

Ryu, H.-S. and J-N. Lee, 2016. Innovation Patterns and Their Effects on Firm Performance. *The Service Industries Journal* **36(3-4)**, 81-101.

Samargandi, N., J. Fidrmuc, and S. Ghosh, 2015. Is The Relationship between Financial Development and Economic Growth Monotonic? Evidence from a Sample of Middle-Income Countries. *World Development* **68**, 66-81.

Sedita, S. R., I. De Noni, and L. Pilotti, 2017. Out of The Crisis: An Empirical Investigation of Place-Specific Determinants of Economic Resilience. *European Planning Studies* **25(2)**, 155-180.

Shen, C.-H. and C.-C. Lee, 2006. Same Financial Development Yet Different Economic Growth ? Why? *Journal of Money, Credit and Banking* **38(7)**, 1907-1944.

Wu, J-L., H. Hou, and S-Y. Cheng, 2010. The Dynamic Impacts of Financial Institutions on Economic Growth: Evidence from The European Union. *Journal of Macroeconomics* **32**, 879-891.

Wurgler, J., 2000. Financial Markets and The Allocation of Capital. *Journal of Financial Economics* **58(1-2)**, 187-214.