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Credit volatility and productivity growth

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Abstract

Research background: The issues of finance-growth nexus and financial instability have attracted considerable attention, but have been studied in isolation. This paper aims at filling this gap by providing insights into the implications of financial instability for long term productivity growth.

Purpose of the article: This paper sheds light on the relationship between credit-to-GDP ratio volatility and the total factor productivity (TFP) growth rate. The impact of systemic banking crises and financial depth on productivity growth is also studied.

Methods: The System GMM estimation of panel data for over 100 countries and spanning the period of 1970–2009 is used. The decomposition of credit-to-GDP ratio into trend and cyclical component is performed using the Hodrick-Prescott filter and a regression analysis with country-specific intercepts and slopes. The data on TFP comes from the Penn World Tables database.

Findings & Value added: TFP growth is negatively affected by credit volatility, mainly in less technologically advanced countries, while financial depth exerts a negative influence on TFP growth in economies with superior technology. Systemic banking crises and the concomitant credit crunches have a negative impact on productivity growth, regardless of the level of technological development. Moreover, the level of human capital, patents and globalization fuel productivity growth. Macroeconomic instability, measured by the rate of inflation, hampers TFP growth.

Introduction

Financial sector depth has been recognized as an important precondition for economic growth. In the most general terms, the development of financial markets is a critical part of the growth process in an environment where acquiring information and making transactions is costly. The primary function of financial intermediaries to ameliorate the problems created by informational and transactions frictions was broken down by Levine (1997) into five functions. Financial development can affect economic growth through channels of capital accumulation and technological innovation because financial institutions:

- ease the trading, hedging, and pooling of risk
- allocate resources
- monitor borrowers
- mobilize savings
- promote specialization (through facilitating the exchange of goods).

Although the view that there is a positive causal effect of financial development on growth is widely held, the conclusion that more financial depth is always better should be stated hesitantly. The instability of financial sector in general and the episodes of financial crises in particular teach us that a financial system malfunction can lead to serious disturbances in the real sector and create large output losses.

The issues of finance-growth nexus and financial instability have attracted considerable attention, but have been studied in isolation. The main objective of this paper is to fill this gap by providing insights into the implications of financial instability for long term growth performance. More precisely, I attempt to shed light on the relationship between credit-to-GDP ratio volatility and the total factor productivity (TFP) growth rate.

The main conjecture of this paper is that the volatility of credit supply exerts a negative influence on productivity growth because it undermines investment in technology improvements. First, investment in technology creation or adoption is risky and bears fruits in the long term. It heavily depends on firm-specific human capital and sustained scientific and engineering efforts. R&D activity cannot be easily suspended and resumed later because hiring and firing costs of the involved personnel are high. The high adjustment costs of R&D investment call for a steady flow of financing.

Secondly, credit volatility can discourage investment in knowledge-intensive assets because they have little potential to serve as collateral. The episodes of relatively wide access to credit which alternate with periods of tight liquidity constraints are favourable to the accumulation of tangible capital. To increase the probability of getting a bank loan when credit be-

comes more accessible, firms may tend to prefer investment in physical capital over R&D investment in intangible knowledge. Hence, credit volatility not only obstructs R&D expenditures smoothing thereby raising adjustment costs, but also is a drag on knowledge-intensive investments which are replaced by accumulation of collateral suitable assets.

Countries may differ with respect to the strength of the channels described above through which credit volatility impairs productivity growth. Firms in emerging and developing countries rely more on bank credit as funding instrument for R&D, while advanced economies have traditionally used private equity and venture capital to finance innovative companies (EBRD, 2014, ch. 4). This implies that credit volatility is much more detrimental to R&D spending and productivity growth in the group of emerging and developing countries suffering from relative technological backwardness and low productivity levels. Firms in advanced economies are more resistant to credit volatility, because they can substitute equity financing for bank loans to undertake productivity-enhancing investment projects.

The reasoning outlined above leads to the hypothesis put forward in this paper, which states that credit volatility undermines innovative activities and reduces the rate of growth of TFP. Moreover, I presume that the hampering effect of intermittent access to credit is more pronounced in developing and emerging countries where R&D expenditures are primarily debt-financed. The aim of this paper is to test this hypothesis using data on 101 countries in the period 1970–2009. Technological progress is path-dependent and, therefore, the rate of growth of TFP is likely to depend on its own lagged value. To study the dynamics of technological change and to address the issue of likely endogeneity of regressors, the System Generalized Method of Moments (GMM) for panel data is employed.

The remainder of the paper is structured as follows. The next two sections review literature on the credit-growth nexus and credit volatility, respectively. They are followed by a section on methods used in the regression analysis. The results of empirical research are presented in the following section.

Credit and growth

The literature on the relationship between financial development and economic growth is vast. This paper focuses on the role of credit in the economy, while the importance of capital market development for growth is beyond its scope. The development of credit markets is usually equated with

their depth, measured by domestic credit to the private sector in percent of GDP.

In empirical research, particular attention has been paid to the issue of reverse causality, which can plague growth regressions with financial development covariates. To deal with this problem, Rajan and Zingales (1998) computed a measurement of manufacturing sectors' dependence on external finance which ensures the exogeneity of financial development variables in growth regressions.

The studies were conducted at the firm as well as sectoral and country levels, and employed cross-country data, panel-data and time-series analysis techniques. The evidence produced using various methodologies does not allow to draw firm conclusions on the importance of finance for growth.

As it was mentioned, the research is plentiful in the area of finance-growth nexus and it was subject to meta-analysis by Arestis *et al.* (2015). They included 69 published papers and collected 1151 observations of the estimated coefficients of financial development in growth regressions. They found the bank-based measures of financial development (e.g. credit-to-GDP ratio) statistically insignificant in all specifications. By contrast, liquid liabilities and market-based variables (e.g. stock market capitalization) were found to be positively associated with growth.

The failure to confirm a positive impact of credit market development on growth could be due to the non-linearity of the relationship between these variables. Arcand *et al.* (2012), using country- and industry-level data, cross-sectional and panel regressions and semi-parametric estimations, detected a non-monotonic relationship between economic growth and the size of the financial system. In particular, they showed that the marginal effect of financial depth on output growth becomes negative when credit to the private sector reaches 80–100% of GDP.

Other examples of recent empirical research that suggest that there might be limits to the benefits of finance include Rioja and Valev (2004), Shen and Lee (2006), and Cecchetti and Kharroubi (2012). Fagerberg and Srholec (2016) who studied post-crisis growth performance conclude that, while access to finance may be essential for growth and development, “too much finance” may be a drag on growth, because it may lead to increased volatility and crowding out of resources from other sectors of the economy.

To understand why high levels of financial development may hamper growth, one can refer to Easterly *et al.* (2000) who investigated the sources of output volatility. They found that credit-to-GDP ratio above the threshold value of around 100% magnifies output volatility. The latter has a negative effect on long-term economic growth which was demonstrated in nu-

merous papers starting with the seminal contribution of Ramey and Ramey (1995).

To deepen the understanding of the finance-growth nexus Beck *et al.* (2014) distinguished between the size of the financial system and intermediation activities. Using OLS regressions, ignoring issues of endogeneity and omitted variables bias, they showed that lending activities measured by the credit-to-GDP ratio increase growth. Conversely, the size of the financial system, proxied by the value added generated by financial sector, had no long-run effect on real sector outcomes.

Evidence on the link between financial development and TFP is less abundant. Beck *et al.* (2000) used cross-country instrumental variable estimator and panel techniques to show that financial intermediaries exert a large, positive impact on TFP growth, while leaving physical capital growth unaffected.

Arizala *et al.* (2009) estimated the impact of the ratio of private credit to GDP on industry-level TFP in 77 countries observed in the 1963–2003 period. They find that TFP growth can accelerate up to 0.6 percent per year in sectors more depend on external finance. By contrast, Fisman and Love (2004) did not confirm that the strength of the growth-promoting effect of financial development hinges in the short-run on the degree of sectors' dependence on external finance. The share of resources allocated to sectors more relying on external finance is positively associated with financial market depth only in the long-run. The authors conjecture that those sectors are more likely to invest in R&D, thereby contributing to TFP growth.

The results of the micro-level studies of the relation between finance and productivity are mixed. On one hand, Dabla-Norris *et al.* (2012) using data from the World Bank survey covering over 14 000 firms in 63 countries concluded that the evidence that the effect of innovation on productivity is mediated through financial markets is weak. On the other hand, Gorodnichenko and Schnitzer (2013), also using data from the World Bank survey, have found that domestically owned firms in transition and developing countries innovate less intensively than foreign-owned companies. They attribute this gap in innovation and productivity to the more severe financial constraints faced by domestically owned firms.

The negative influence of excessive financial development was corroborated by Coricelli *et al.* (2012) at the firm level. Estimates of the threshold regression model for a sample of Central and Eastern European countries confirmed that TFP growth increases with book leverage until the latter reaches a critical threshold beyond which leverage becomes “excessive” and lowers TFP growth.

Credit volatility

The financial crisis demonstrated the importance of the interaction between the “financial cycle” and real sides of the economy. It triggered research on the booms and busts of credit supply and asset prices which can lead to serious macroeconomic distress. Drehman *et al.* (2012) documented the marked increase in the length and amplitude of the financial cycle since the mid-1980s; the financial cycle seems to be much longer than the traditional business cycle. Financial cycle peaks are very closely associated with financial crises and business cycle recessions are much deeper when they coincide with the contraction phase of the financial cycle. The importance of credit market shocks in driving global activity during the global recession of 2007–09 was corroborated by Helbling *et al.* (2011) in the G–7 countries.

Fluctuations of the supply of credit, even if they don’t give way to financial turmoil, have a bearing on the real economy. Firstly, instability of credit supply impinges on R&D and technology adoption expenditures smoothing. Transitory shocks to finance may entail significant costs of firing and hiring of highly trained R&D personnel and disrupt team-work on long-term innovative projects. Secondly, credit supply volatility may amplify business cycle. Higher output volatility in turn translates into higher degree of uncertainty that induces agents to postpone decisions. This is particularly true of risky and irreversible investment in development of new or adoption of existing technologies.

According to Hall and Lerner (2010), fifty per cent or more of R&D spending is the wages and salaries of highly educated scientists and engineers. This fact makes R&D investment different from ordinary investment. Because part of the resource base of the firm itself disappears when R&D personnel leaves or is fired, firms tend to smoothen their R&D spending over time, in order to avoid having to lay off knowledge workers. In other words, R&D investment has high adjustment costs (Hall *et al.*, 1986; Lach & Schankerman, 1988).

Pakes and Nitzan (1983) described optimal labor contracts designed specifically to retain R&D workers to reduce appropriation problems. Bernstein and Nadiri (1989) estimated returns for R&D and physical investment as well as the marginal adjustment costs for these inputs for firms. They found the latter to be higher than the marginal adjustment costs for physical investment. Brown and Petersen (2011) offered direct evidence that U. S. firms relied heavily on cash reserves to smooth R&D spending during the 1998–2002 boom and bust in stock market returns. For Korea, Shin and Kim (2011) document that firms, in particular the young ones, use

more cash holdings to smooth R&D investment during a bear market than a bull market.

Recently, Arvanitis and Woerter (2013) have investigated firm characteristics that are responsible for anti-cyclical R&D investment behavior of manufacturing firms in Switzerland. They found that firms which benefit from low opportunity costs through anti-cyclical R&D investments are relatively large. That indirectly points to the importance of credit cyclicity because large firms have wider access to external finance and have less financial restrictions in recessions. The evidence on the importance of liquidity constraints as the cause of R&D cyclicity in U.S. manufacturing industries was provided by Ouyang (2011) and in French firms by Aghion et al. (2012).

The impact of financial shocks on TFP growth was examined by Estevão and Severo (2010). Financial shocks, defined as increases in the costs of funds, had a statistically significant and economically meaningful negative impact on TFP growth in 31 U.S. and Canadian industries between 1991 and 2007. The authors suggested that financial shocks distort the allocation of factors of production across firms.

Research methodology

In studying productivity growth, the procedure that consists in writing regression equation as a dynamic panel data model in first differences has important advantages over simple cross-section or other panel estimation methods. First, unobserved time-invariant country specific effects are removed. Second, the use of instrumental variables allows parameters to be estimated consistently in models where some of the explanatory variables are endogenous. One prominent way to take advantage of the virtues of the dynamic panel data model in first differences is to apply first-differenced generalized method of moments (GMM) estimators. I adopt this approach below.

The basic idea behind the ‘system’ GMM estimator is to estimate a system of equations in both first-differences and levels, where the instruments used in the levels equations are suitably lagged first-differences. Blundell and Bond (1998) showed that the first-differenced GMM estimator might be subject to a large downward finite-sample bias, particularly when the number of time periods available is small, which is a common feature of empirical studies that use longer period-averages to remove business cycle effects from the data. By imposing an additional set of moment restrictions which allow the use of lagged first-differences of the series as instruments

for equation in levels, Blundell and Bond obtained a linear GMM estimator better suited for estimating autoregressive models with persistent panel data, which has superior finite sample properties than the GMM Arellano and Bond (1991) estimator.

To be more specific, the empirical model estimated in the next section has the following form:

$$TFP_{it} = \alpha_t + \beta \cdot TFP_{i,t-1} + \lambda \cdot credit_volat_{i,t-1} + \gamma \cdot x_{it} + d_i + e_{it}, \quad (1)$$

where i and t , is respectively, the country and time index. The dependent variable, TFP , is the log of total factor productivity taken from the Penn World Table 9.0 database of Feenstra *et al.* (2015). The explanatory variables set includes the period-specific effects, α_t , lagged value of the regressand, a measure of credit volatility, $credit_volat$, the vector of control variables, x_{it} , and the unobserved country-specific effects, d_i . The last term denotes the error term. All variables were averaged over the 5-year intervals in the 1970–2009 period. I used the lagged value of a measure of credit volatility on the premise that access to external financing which affects the level of investment in R&D may have only delayed effect on the outcome, that is productivity growth.

The moment conditions imposed by the System GMM technique require stationary means of all the series. This assumption, especially in the case of TFP , seems to be inconsistent with an empirical model of productivity growth but the problem is alleviated by the inclusion of 5-year intervals dummies, α_t , which allow for a common world rate of long-run technological progress.

To detect problems with instrument validity, the Hansen test of over-identifying restrictions was applied, and the corresponding p-values are reported. Since finite samples may lack adequate information to estimate a variance matrix of the moments and a large number of instrument may bias the results, I report the instrument count. In all regressions, the lagged values of all explanatory variables were used as instruments. The first and further lags of variables in levels were used as instruments for equation in differences, and lags of variables in first differences were used as instruments for equation in levels.

The consistency of estimators is conditional on the assumption that the error term e_{it} is not serially correlated. Then, the first-differenced residuals should display a negative first-order serial correlation, but not second-order serial correlation. I report the p-value of the Arellano-Bond test of first- and second-order serial correlation.

The variable of interest is the measure of credit volatility, *credit_volat*. To ensure the robustness of my results, I used two methods for decomposing the credit-to-GDP series into the cyclical and trend components. The first consists in using the Hodrick-Prescott filter. Provided that the duration of the financial cycle is at least twice as long as the business cycle (Drehmann *et al.*, 2012), the trend should be extracted with the lambda parameter equal to 125 000 for quarterly data (Drehmann *et al.* 2010). Following the Ravn and Uhlig (2002) rule, the value of the lambda parameter for annual data which I use is 488. The standard deviation of the cyclical component is used as the first measure of credit volatility.

The second way of obtaining the trend and cyclical component of the credit-to-GDP series is based on a regression analysis. I regressed the credit-to-GDP ratio on the level of GDP of a country and the rate of growth of per capita GDP. As argued by Djankov *et al.* (2007), the total GDP affects financial market depth, because credit markets might require fixed institutional costs to function, which are paid only when the total economy is large enough. Turning to per capita GDP growth rate, it can be conjectured that faster growing economies could have greater demand for credit. This simple regression was estimated individually for each country in the sample, thus allowing for country-specific slopes and intercepts. The latter control for unmeasured time-invariant characteristics, such as institutional environment in which financial intermediaries operate. The fitted value of the regression is regarded as an alternative measure of the trend of credit-to-GDP ratio, while the standard deviation of the residual is interpreted as credit volatility. To improve the precision of measuring volatility and trend components of the credit-to-GDP ratio, both methods were applied to data spanning years 1960–2009.

Financial crisis is an extreme manifestation of credit volatility because its inherent feature is a credit crunch. To account for a sudden reduction in the availability of loans I include among regressors, a dummy variable *crisis* coded 1 for all systemic bank crises episodes. The data comes from Laeven and Valencia (2013), who defined a crisis as systemic if two conditions are met: significant signs of financial distress in the banking system are observed, and significant banking policy intervention measures are implemented.

The selection of control variables was guided by the results of the empirical studies on the source of cross-country differences in TFP of Senhadji (2000), Isaksson (2007) and Tebaldi (2016). The set of covariates includes the lagged trend value of credit-to-GDP, *credit_trend*, which was obtained by the methods described above. To measure labor quality, labeled *human*, I relied on the human capital index from the Penn World

Table 9.0 database which is based on the average years of schooling and an assumed rate of return to education. The variable called *infl* is the rate of inflation intended to capture overall macroeconomic stability. To account for international technology diffusion, I included the lagged value of the updated KOF index of economic globalization of Dreher (2006), *global*, which combines measures of trade and FDI flows. Finally, the impact of R&D investments output is gauged by the first difference of the number of patents, labeled *patents*, granted by the U.S. Patent and Trademark Office.

Empirical results

Table 1 reports the results of the basic regression estimates with two alternative measures of credit volatility. In the first column, the standard deviation of the cyclical component of the credit-to-GDP series was used as a measure credit volatility, while the regression residual was used in the second column. For the sake of clarity and readability, the value of estimated coefficients and standard errors of period dummies have been omitted.

It stems from Table 1 that all control variables' parameters have the expected sign. Human capital, globalization and R&D output measured by the number of patents are beneficial to the productivity growth, while macroeconomic instability proxied by inflation has a detrimental effect on it. Credit volatility, regardless of its measure, seems to be irrelevant for TFP growth. On the other hand, systemic banking crises exert a negative influence on productivity. The same is true of the trend value of credit. It should be noted, that the *p*-value of the Hansen test of overidentifying restrictions in column (2) suggests that the choice of instruments is not fully accurate.

The insignificance of credit volatility and the negative sign of the estimated coefficient of the trend value of credit allow rejecting the hypothesis that credit instability hampers productivity growth worldwide and that access to credit is a precondition for R&D investment and technology improvements. I argue, however, that the results showed in Table 1, despite being based on panel data estimation, mask cross-country differences stipulated in the second hypothesis.

According to the second hypothesis pursued in this paper, less developed and technologically advanced countries' R&D activities are more dependent on bank financing, thereby more vulnerable to credit shocks. To shed light on this issue, I used the level of TFP relative to the US to distinguish less and more technologically advanced countries. More precisely, less (more) technologically advanced countries have the relative TFP level below (above) the sample average. Next I constructed two variables for

each of the credit volatility and trend credit variables. For instance, *credit_volat_low* has the value of *credit_volat* for less technologically advanced countries and zero otherwise. Its high-tech counterpart, labeled *credit_volat_high* is equal to *credit_volat* for more technologically advanced countries and zero otherwise. Similarly, *credit_trend_high* and *credit_trend_low* are equal to trend of credit-to-GDP ratio for more and less, respectively, technologically advanced countries and zero otherwise.

It turned out that *credit_volat_high* and *credit_trend_low* were not statistically significant. This is why Table 2 displays the results of model specifications without these variables but with credit volatility variable for less technologically advanced countries (*credit_volat_low*) and trend of credit-to-GDP for countries with superior technology (*credit_trend_high*).

The diagnostic tests results ensure that the residuals display the first-order, but not the second-order serial correlation, and that the choice of instruments is accurate. Estimates in Table 2 reveal that credit volatility undermines productivity growth only in less technologically advanced countries. It should be noted that this result is significant, but only at the 10 percent level.

Second, the trend level of credit impairs productivity growth in technologically advanced countries. This finding is not at odds with the literature on the non-linear relation between credit market depth and economic growth. Technologically sophisticated countries are usually more financially developed. It could be argued that the negative consequences of “excessive” financial development in terms of volatility and resource allocation discussed above are more pronounced in technologically advanced countries. In the group of countries with below average level of technology, the positive effects of financial depth in terms of wider access to external financing are offset by the negative effects. For this reason, the trend value of credit-to-GDP ratio was statistically insignificant in less technologically advanced countries.

Conclusions

The System GMM estimation results obtained in this paper, using data for over 100 countries and spanning period 1970–2009, support the hypothesis that TFP growth is negatively affected by credit volatility mainly in less technologically advanced countries. I also show that financial depth measured by the credit-to-GDP ratio exerts a negative influence on TFP growth in economies with superior technology. Credit volatility does not affect productivity growth in more technology advanced countries and the trend

value of credit-to-GDP ratio hampers TFP growth. These results are robust to the decomposition method applied to obtain the cyclical and trend components of the credit-to-GDP ratio.

Systemic banking crises and the concomitant credit crunches were found to have a negative impact on productivity growth, regardless of the level of technological development. An abrupt and unpredictable narrowing of access to external financing seems to impinge more heavily on R&D activities than the mere fluctuation of credit around trend.

Moreover, the regression analysis revealed that the level of human capital, number of patents granted and globalization fuel productivity growth. Macroeconomic instability, measured by the rate of inflation, hampers TFP growth. The overall conclusion is that credit and macroeconomic stability is conducive of productivity growth.

The main message which emerges from the empirical results presented in this paper is that access to credit is not the only characteristic of financial markets which impacts on growth of nations. The abundant analyses of the link between financial development and growth should be complemented with studies of the importance of stability of financial systems for accumulation of factors of production and technological progress. This paper is a first step in this respect, as it focuses on the relationship between credit volatility, rather than its availability, and TFP growth.

The future work in this area would include other aspects of financial instability, such as credit market disequilibrium, speculative bubbles in asset markets, or exchange rate crises. It would be also interesting to investigate the impact of credit volatility on the accumulation of factors of production in general and physical and human capital in particular. Analyses of the relationship between credit volatility and productivity growth at the firm level could be another fruitful path for future research.

In terms of policy recommendations, the findings presented in this paper suggest that the regulatory framework which imposes capital requirements on the banking sector should not be focused exclusively on excess aggregate credit growth. Efforts should also be made to reduce the risk that the supply of credit will be constrained by a countercyclical capital buffer regime. This advice is based on the main conclusion of this paper that all unexpected changes, i.e. both increases and decreases, in credit supply may impinge on technological progress.

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Annex

Table 1. Determinants of (the log of) TFP in the 1970–2009 period

Volatility measure obtained using:	(1) Hodrick-Prescott filter	(2) regression residual
TFP_lagged	0.798*** (0.0513) [0.000]	0.770*** (0.0507) [0.000]
credit_volat	-0.00204 (0.00152) [0.183]	-0.00200 (0.00128) [0.120]
credit_trend	-0.000648** (0.000260) [0.014]	-0.000798** (0.000315) [0.013]
crisis	-0.0430** (0.0189) [0.025]	-0.0342** (0.0171) [0.049]
infl	-6.43e-05** (2.70e-05) [0.019]	-5.95e-05* (3.06e-05) [0.055]
human	0.0452 (0.0376) [0.232]	0.0328 (0.0300) [0.276]
global	0.00223* (0.00114) [0.053]	0.00212** (0.000852) [0.014]
patents	3.32e-06** (1.50e-06) [0.029]	4.22e-06** (1.91e-06) [0.029]
Period dummies	YES	YES
Observations	649	649
Number of countries	101	101
F [p-value]	26.27 [0.0]	28.93 [0.0]
Hansen [p-value]	79.88 [0.135]	85.62 [0.073]
Number of instruments	86	87
AR2 test p-value	0.151	0.153
AR1 test p-value	0.00579	0.00754

Note: Standard errors in parentheses, p-values in square brackets; *** p<0.01, ** p<0.05, * p<0.1. Instruments for first differences equation: Standard: First differences of period dummies and the share of ores and metals exports in total exports; GMM-type: lagged (one period and more) values of all (except period dummies) independent variables. Instruments for levels equation: Standard: period dummies and the share of ores and metals exports in total exports; GMM-type: first differences of all (except period dummies) independent variables.

Table 2. Determinants of (the log of) TFP: credit volatility in less technologically advanced countries

Volatility measure obtained using:	(1) Hodrick-Prescott filter	(2) regression residual
TFP_lagged	0.797*** (0.0488) [0.000]	0.793*** (0.0443) [0.000]
credit_volat_low	-0.00447* (0.00259) [0.088]	-0.00378* (0.00216) [0.082]
credit_trend_high	-0.000714*** (0.000232) [0.003]	-0.000785*** (0.000241) [0.002]
crisis	-0.0369** (0.0165) [0.028]	-0.0340* (0.0179) [0.061]
infl	-6.32e-05** (2.97e-05) [0.035]	-5.98e-05** (2.76e-05) [0.033]
human	0.0337 (0.0297) [0.260]	0.0438* (0.0236) [0.067]
global	0.00226** (0.000994) [0.025]	0.00219** (0.000871) [0.013]
patents	3.86e-06** (1.67e-06) [0.023]	3.54e-06** (1.45e-06) [0.016]
PERIOD DUMMIES	YES	YES
Observations	649	649
Number of countries	101	101
F [p-value]	33.37 [0.0]	35.18 [0.0]
Hansen [p-value]	78.56 [0.179]	77.89 [0.193]
Number of instruments	87	87
AR2 test p-value	0.186	0.178
AR1 test p-value	0.00317	0.000317

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Instruments for first differences equation: Standard: First differences of period dummies and the share of ores and metals exports in total exports; GMM-type: lagged (one period and more) values of all (except period dummies) independent variables. Instruments for levels equation: Standard: period dummies and the share of ores and metals exports in total exports; GMM-type: first differences of all (except period dummies) independent variables.

List of the countries in the sample. A star, “*”, indicates a country which in the majority of periods was classified as a low-technology country

Argentina*, Armenia*, Australia, Austria, Bahrain, Barbados, Belgium, Benin*, Bolivia*, Brazil*, Bulgaria, Burkina Faso*, Cameroon*, Canada, Chile, China*, Colombia*, Costa Rica*, Croatia, Cyprus, Czech Republic*, Côte d'Ivoire*, Denmark, Dominican Republic*, Ecuador*, Egypt, Estonia*, Fiji*, Finland*, France, Gabon, Germany, Greece*, Guatemala, Honduras*, Hungary*, Iceland, India*, Indonesia*, Iran, Ireland, Israel, Italy, Jamaica*, Japan, Jordan, Kazakhstan*, Kenya*, Kuwait, Kyrgyzstan*, Latvia*, Lithuania, Luxembourg, Malaysia*, Malta*, Mauritania*, Mauritius, Mexico, Moldova*, Mongolia*, Morocco, Namibia, Netherlands, New Zealand, Nicaragua*, Nigeria, Norway, Panama, Paraguay*, Peru*, Philippines*, Poland*, Portugal*, Qatar, Republic of Korea*, Romania*, Russian Federation*, Saudi Arabia, Senegal*, Serbia*, Singapore, Slovakia*, Slovenia, South Africa, Spain, Sri Lanka*, Sudan, Swaziland, Sweden, Switzerland, Tanzania*, Thailand*, Trinidad and Tobago, Tunisia, Turkey, Ukraine*, United Kingdom, United States, Uruguay*, Venezuela, Zimbabwe.