Assessing the Effects of Trade-Induced Technology Imitation on Economic Growth in Africa

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Abstract

This study aims to quantify the effects of trade-induced technology imitation (proxied by the share of imports in the "easy imitation" SITC category) on economic growth in Africa, using a production function approach in a panel system GMM estimator. Indicators of trade-induced technology imitation have been built on the Standard International Trade Classification (SITC) using raw data from the United Nations' COMTRADE Statistics. The findings suggest that conditional on the level of the human capital index, economic growth tends to be greater in countries with higher ratios of technology imitation. Another notable finding is that the lower the level of GDP per capita, the greater the growth effects of technology imitation relative to other forms of technological progress. In addition to explaining how trade-induced technologies influence economic growth in Africa, the paper explores a definition and measurement of technology imitation.

JEL: O47, O33, O32

1. Introduction

Economic theories and development experiences alike show that countries that have successfully caught up with the advanced economies have typically gone through a process of significant technological progress. In this connection, endogenous theories of growth support the view that the cumulative R&D activities in developed countries contribute to the stock of knowledge, which enhances the productive capacity of the economy on the one hand and generates spillovers on the other hand. These spillovers, in turn, act as an external effect in enhancing the productive capacity of other countries through international trade (Evenson and Singh, 1997). Through international trade, developing countries adapt and develop technological capability via technology diffusion from the technological leaders (Coe and Helpman, 1995; Coe et al., 1997; Keller, 1998).

The economics literature and policy practice provide ample evidence of the link between technology diffusion and certain types of imported inputs (Eaton and Kortum, 1996; Keller, 2001). In addition, the economic rationale for the high intensity of imitation is addressed in Poyago-Theotoky (1998) and Barro et al. (2003), among others. Arguably, developing countries

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tend to catch up to the industrialized countries because imitation and implementation of discoveries are cheaper than innovation. This mechanism tends to generate convergence even if diminishing returns to capital or to R&D do not apply (Barro et al. 2003). Furthermore, the practice of technology imitation has been the cornerstone of development experiences in Asia, in that initially, countries have frequently relied on successful imitation[2] of foreign technologies to achieve indigenous technological development (Carolan et al., 1998).

Despite the central role imitation has played in development and technology catching-up, however, it has received only modest attention in explanations of economic growth (Niosi, 2012). Even more worrisome, little empirical research exists on the extent to which technology imitation has occurred via trade and how this affects economic growth in developing countries (Datta and Mohtadi, 2006). The lack of empirical research on this critical issue stems from measurement and data constraints associated with the concept and practice of imitation. Although some of these constraints may still remain, recent progress in international trade statistics (e.g., the United Nations' COMTRADE Statistics) has made it possible to mine the data and come up with acceptable proxy indicators for developing countries.

Taking advantage of the advances in trade statistics for African economies, this research aims to assess the growth effects of trade-induced technology imitation across African countries. In particular, the study tries to evaluate the degree to which technology imitation variables predict economic growth in a panel of African countries. To do this, we built a "trade-induced imitation"[3] indicator and incorporated it into an augmented growth model that follows Connolly (1997). This model is then empirically tested using a panel system generalized method of moments, GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Our findings suggest that conditional on the level of the human capital index, economic growth tends to be greater in countries with higher ratios of technology imitation. Another notable finding is that the lower the level of GDP per capita, the greater the growth effects of technology imitation relative to other forms of technological progress.

The rest of the paper is organized as follows. The next section contains a brief overview of the related literature. Sections 3 and 4 cover methodological and data considerations, respectively. Section 5 presents the empirical results, and the last section concludes.

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[2] Imitation as defined here comprises both "replica" (imitation by legal means, through licenses obtained from the pioneer, or informal imitation, through copying of old and unprotected technologies) and "mimicry" (produced through reverse engineering) (Ulhoi, 2012).

[3] The term "trade-induced technology imitation" is used in this paper to refer to an increase in technological capability of firms or countries as a byproduct of their importing/trading activities, gauged by their trading performance in certain types of technology-intensive product categories.

2. Literature Overview

A considerable amount of research has been done on the trade–growth nexus, especially in its connection to international technology spillovers. The related literature and development experiences alike show that countries that have successfully caught up with the advanced economies have typically gone through a process of significant technological progress (e.g., Matsuyama, 1992; Edwards, 1993). Technological progress has gained even greater prominence as the most critical contributor to economic growth since the emergence of endogenous growth theories.

While early endogenous growth models such as that of Romer (1986; 1990) present R&D as a critical engine of economic growth, this view only weakly reflects the context of less-developed countries. Arguably, the less-developed countries undertake little R&D expenditure and thus cannot add much to innovation or technological progress via the R&D channel (Hausmann and Rodrik, 2003), but firms in less-developed countries reap the benefits of innovation through international trade or other forms of technology spillovers. Technology spills over through product variety, scale, and learning (e.g., Lucas, 1988; Matsuyama, 1992). Agosin (2007) points out that technologically under-developed countries upgrade their technology capacity by imitating and adapting existing products. Similarly, Mendoza (2010) shows that the structure most conducive to a developing country's rapid industrialization and technological catch-up would be one in which there is trade in intermediate goods and final products with growing variety and technology content. Furthermore, models in the product cycle literature (Vernon, 1966; Krugman, 1979; Grossman and Helpman, 1991) show that diversity of export products in developing countries is achieved through a complementary processing. That is, innovation is done in the North while the South predominantly focuses on imitation, processing and exporting of finished products (using the South's cheap-labor advantage). In sum, less-developed countries initially reduce their technology gap through import-embedded technology and then proceed to imitation (Jovanovic and MacDonald, 1994).

Notably, technology imitation is not only a theoretical possibility but also a developmental fact. For many East Asian economies that were lagging behind in terms of technology, the imitation and adaptation of advanced technologies provided valuable opportunities to catch up to more advanced countries (Lee, 2015). Hu (2015) assesses the dynamic process of technological imitation in East Asian economies, particularly in South Korea, and the role of policies and institutions for technological development, and highlights four major contributing success factors: the proactive role of government, the high quality of human capital in science and engineering, a well-developed link to a global production network, and (more controversially) an international environment that was lax in enforcing intellectual property rights.

The literature on growth recognizes other engines of economic growth that cannot be ignored. Factors such as institutions, innovational effort, and education, among others, have been widely cited. In regard to the latter, technology adoption by developing countries can be enhanced (in terms of economic growth) when the country has a higher level of human capital, which increases its absorption capacity (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994). A minimum threshold of human capital is needed for technology imitation to be successful (Vandenbussche et al., 2006; Teixeira and Fortuna 2011). In this respect, panel data analysis indicates that the most important determinant of the speed with which a country adopts technologies is that country's human capital endowment (Comin and Hobijn, 2003).

The empirical literature on the link between technology imitation and per capita income patterns is scant and largely limited to the broad issue of export diversification. For instance, in a conventional cross-sectional country growth regression, Al-Marhubi (2000) adds various measures of export concentration to the basic growth equation and finds that export diversification promotes economic growth. Similarly, Hausmann et al. (2007) point to a positive link between export diversification, mostly in different forms of manufactured items, and economic growth, and yet the caveats in regard to these studies, including issues of potential endogeneity and a lack of commonly agreed-upon indicators, are now well known (Edwards, 1993; Rodriguez and Rodrik, 2001). Various indicators of trade-related spillovers that have been used in empirical studies are very crude proxies for examining what could be a complex process of outward-oriented industrialization anchored in a dynamic and expanding manufacturing sector (Mendoza, 2010).

More recent empirical studies have begun to zero in on specific links that might shed further light on the nexus between trade and growth, including links between the predominance of manufactures and technology-intensive items in exports and more sustained growth spells. Hausmann et al. (2006) develop an indicator that measures the productivity level associated with a country's export basket. This measure reflects the idea that countries that produce high-productivity goods enjoy faster growth than countries with lower-productivity goods (Hesse, 2008).

However, few of these technology-intensive trade flows have been used to examine the link between trade and economic growth in low-income countries. We have used import performance in the "easy-imitation category" as an attempt to both extend the empirical literature and evaluate the degree to which technology imitation variables predict economic growth in a panel of African countries. The main motivation of this paper is to determine whether—and to what extent—a framework of trade-induced technological progress could be used to engineer technological progress and economic growth in Africa. It is assumed that the higher the level of technology imitation in international trade between two countries, the higher the probability that industries in the country with lesser technological knowledge will converge to those in the country with greater technological knowledge.

3. Methodology

The reference model follows an augmented growth model of Connolly (1997), wherein the engine of growth lies in learning by doing and trade-induced learning. The empirical estimation was based on panel data. The use of panel data to investigate the growth effects of trade or technological progress has been a common trend in recent years. In this study, we specifically use the generalized method of moments (GMM) system estimator suggested by Arellano and Bover (1995) and later developed by Blundell and Bond (1998) and Blundell et al. (2000). This estimator has the potential advantages of minimizing the bias which is due to estimation of dynamic panel models, exploiting the dynamic and time-series properties of the data, controlling for the unobserved country-specific effects, and correcting for the bias that arises from the possible endogeneity of the explanatory variables. Consider the following model:

$$y_{i,t} = \delta y_{i,t-1} + X_{it}\beta + \alpha_i + u_{i,t} \tag{1}$$

$$E(\alpha_i) = E(u_{it}) = E(\alpha_i u_{it}) = 0,$$

where y is the reported economic growth of country i in year t, X includes all other explanatory variables, α_i is the country-specific unobserved heterogeneity that varies across countries but not over time for any country, and $u_{i,t}$ is the idiosyncratic error term, which varies by country and over time. The country-specific unobserved heterogeneity is allowed to be correlated with the explanatory variables, and the idiosyncratic error term may also be correlated with some of those variables.

One problem with estimating equation (1) via the method of ordinary least squares (OLS) is the endogeneity of the lag in economic growth. If a country in Africa experiences a large positive growth shock for a reason not modelled, the shock is subsumed into the error term. The country-specific unobserved heterogeneity will appear larger over the entire time span of the data (since it does not vary from one year to another), and in the year following the growth shock the lag in economic growth will also be large and positive. This positive correlation between the error term and the lag in economic growth would yield inconsistent and biased OLS results—results that in this case are biased upwards.

An initial attempt to purge the fixed effects might consist of estimation of panel-data fixed effects or least-squares dummy-variable regression (entering a dummy variable for each country). However, Roodman (2006) shows that this will not entirely remove "dynamic panel bias" and in fact would result in downward bias on the lag in economic growth in the aforementioned example. One strategy for purging the unobserved heterogeneity is to difference the data. Equation (1), when first-differenced, yields the following:

$$y_{i,t} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (X_{it} - X_{i,t-1})\beta + (u_{i,t} - u_{i,t-1}) \qquad (2)$$

that is,

$$\Delta y_{i,t} = \delta \Delta y_{i,t-1} + \Delta X_{it}\beta + \Delta u_{i,t}$$

The differencing eliminates the country-specific unobserved heterogeneity. However, the lag in economic growth remains endogenous, because $y_{i,t-1}$ is correlated with $u_{i,t-1}$. Other explanatory variables may also be correlated with the lag in the error term if they are not strictly exogenous and are only contemporaneously exogenous in the non-differenced equation. Fortunately, even larger lags in the explanatory variables are exogenous and can be used as instruments.

As Roodman (2006) explains, the first-differenced transformation is best used for strongly balanced panels. In an unbalanced panel, if $y_{i,t}$ is missing, then both $\Delta y_{i,t}$ and $\Delta y_{i,t+1}$ will also be missing. Since our data are unbalanced (in any given year, a number of countries have missing data), we use a second option for purging the unobserved heterogeneity. This method, called "orthogonal deviation" (Arellano and Bover, 1995), subtracts from $y_{i,t}$ the mean of all future available values. This method mitigates data loss and makes all the lagged variables available as instruments. We will denote data transformed by orthogonal deviation as follows:

$$\tilde{y}_{i,t} = \delta\tilde{y}_{i,t-1} + \tilde{X}_{it}\beta + \tilde{u}_{i,t} \qquad (3)$$

The dynamic panel *system* GMM estimator employed here incorporates equation (1) in the "orthogonal deviations" *and* in the regression in levels as a system, to increase efficiency. For the level regression, since the unobserved heterogeneity is not purged, instruments must be used. The instruments are the lagged differences in the endogenous explanatory variables. This is based on the assumption that, while the unobserved heterogeneity may be correlated with the levels of the explanatory variables, it will not be correlated with their differences. The following moment conditions are satisfied for the second part of the system (the regression in levels):

$$E[(y_{i,t-1} - y_{i,t-2})(\alpha_i + u_{i,t})] = 0 \tag{4}$$

$$E[(X_{i,t-1} - X_{i,t-2})(\alpha_i + u_{i,t})] = 0 \tag{5}$$

The three moment conditions (equations (3) through (5)) are used to implement the dynamic panel system GMM estimation, producing consistent parameters.

4. Data considerations

The datasets for our key variable (technology imitation) have been built from raw data extracted from the United Nations' COMTRADE (2015) 5-digit SITC **(**Standard International Trade Classification) codes. Technology imitation is gauged by the trading performance of countries/firms in certain types of technology-intensive product categories. The starting point in measuring such performance would be to consider imports of goods in the technology-intensive categories, that is, Classes 5, 7, 86, and 89 in SITC (Revision 4). These classes include machinery and transport equipment, instruments (optical, medical, and photographic), watches, clocks, and miscellaneous manufactured goods (such as office equipment, which in later years has included computers). The concern with this category of items is that these commodity classes include high-technology goods, and thus are not likely to be imitable in low-income countries such as those in Africa. Therefore, following the classification in Yilmaz (2002), we restricted the above classes of commodities to low-technology–intensive items, which comprise classes 51, 52, 54.1, 58, 59, and 75 in Revision 4 of SITC (for further information, see Yilmaz (2002)), and built our first proxy of technology imitation (Imitation 1).

While our first proxy of technology imitation is built from imports of products in the aforementioned-import classes, this does not necessarily indicate that a country is actually succeeding in bridging its technological gap. To indirectly assess the degree to which a country is succeeding in imitating foreign technology, we can look at the expansion of its share of exports in the easy-imitation technology category. This is our second proxy of technology imitation (Imitation 2), which uses exports in the same categories as those used in Imitation 1.

The initial datasets comprise time-series data for 44 sub-Saharan African countries, which are sourced as indicated in Table 1. As a result of limitations in those datasets, only 26 countries were included in the econometric regression. Regression-wise, the dependent variable is the GDP per capita growth rate, defined as "the sum of the gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products" (World Bank, 2014). Following Barro (1997), the benchmark model includes physical capital investment (defined as "real gross domestic investment (private and public) as a percentage of GDP") next to the imitation proxy, as independent variables.

Moreover, some additional variables must be considered to control for other factors that could potentially lead to spurious correlation between the independent variable and the imitation proxies. Specifically, secondary school enrollment and population growth are added as control variables. In this regard, a finding that trade-induced imitation contributes positively to economic growth could simply reflect a population bonus, rather than spillovers from imitation, because population growth tends to encourage competition in business activities and expands the market's potential. Expansion of a market encourages entrepreneurs to set up new businesses or expand existing ones by incorporating new ideas learned via trade-induced technology imitation and other avenues. For this reason, the population growth variable was included in the regressions. Similarly, although it is widely assumed that less-developed countries do not spend on R&D, it is nonetheless true that they do engage in some forms of innovation (broadly defined). Hence, since innovation performance affects the domestic imitation environment, an innovation index was included in the regressions.

Table 1. Standard growth control variables (Barro, 1997)

Variables	Sources
1- Real GDP per capita, constant 2005 $	Summers and Heston (7.1); missing data from World Development Indicators
2- physical capital Investment	Summers and Heston (7.1); missing data from World Development Indicators
3- Education index	World Development Indicators 2014, CD-R, World Bank
4- Imitation 1	UN's COMTRADE Database, raw data source
5- Imitation 2	UN's COMTRADE Database, raw data source
6- Population	World Development Indicators 2014, CD-R, World Bank
7-Innovation index	World Development Indicators 2014, CD-R, World Bank

5. Empirical results

A central issue that had to be addressed before making the appropriate econometric specification is to test the stationarity or unit root requirement. This was done by following the approach of Im et al. (1995), who developed a panel unit root test for the joint null hypothesis that every time series in the panel is nonstationary. Results of this test are not reported (they are available upon request), but in every case we rejected the possibility of a unit root in favor of stationarity (these results were also confirmed by the Fisher–ADF and Fisher–PP panel unit root tests) at the 5 percent significance level, and it was deemed safe to proceed with the system GMM estimation.

The results of the system GMM estimation are presented in Table 2. Looking at the benchmark model (column 1), the control variables of the augmented growth model maintain their expected influence, and all test statistics confirm the validity of our instruments. Also, the investment rate as a share of GDP has a positive and highly significant coefficient. As it turns out, population growth has a significantly negative effect on GDP per capita growth rates, and the influence of investment in education is positive and significant at the conventional 10 per cent level. Not surprisingly, the coefficient of the innovation index shows that innovation is not significant, both in the benchmark model as well as in the specification that includes technology imitation. In fact, dropping innovation in the subsequent models improved the efficiency of the estimation results.

All realizations of the potentially endogenous explanatory variables, lagged by two or more periods, have been included as instruments, and the Sargan/Hansen test of overidentifying restrictions confirms the joint validity of our instruments. The p-value of the Arellano–Bond test for second-order correlation in differences (the Ar(2) test) rejects first-order serial correlation in levels. Having established a valid benchmark, we subsequently included our main variable of interest, technology imitation, in three variants (Imitation 1, the value of Imitation 1 lagged by one period, and Imitation 2).

Inclusion of our alternative measures of technology imitation, Imitation 1 or its lagged value Imitation 1 ($t-1$), fundamentally changes the regression results for the impact of investment on GDP per capita growth (columns 2–6). Notably, the coefficient of investment increased from 0.107 in the benchmark model to over 0.160 in subsequent models. Also, Imitation1 has a positive coefficient and is significant at the 10 percent and 1 percent level of confidence, respectively in Columns (2) and (5). At the same time, the coefficient of lagged Imitation 1($t-1$), which is 0.1065, is not only significant at the conventional 5 percent level but also of greater magnitude than the coefficient of Imitation 1 *per se*. This result can be interpreted to mean that an increase in the ratio of the volume of easy-imitation “import category” to total imports in the previous period by one unit at the mean is associated with an increase in GDP per capita growth of 0.1065 percentage points over the current period.

Surprisingly, in contrast to Imitation 1, the results reported in column 4 suggest that the coefficient of Imitation 2 (proxied by the export classes defined earlier) is not significant and thus that that variable has no impact on economic growth. It might be argued that for African countries the preconditions for the realization of a positive nexus between technology-intensive exports, income, and growth is not yet being achieved.

The evidence established so far has been for the total sample, including both middle-income countries such as South Africa or Mauritius and LICs (low-income countries; based on the World Bank's classification) such as Malawi or the Democratic Republic of the Congo. The question arises, Is the positive influence of trade on income growth robust for LICs only? Columns 5 and 6 shed some light on this issue by showing the results for a subsample of 22 African countries classified as LICs. As shown in Columns 5 and 6, the coefficients of Imitation 1 and Imitation 1($t-1$) are much higher—and significant at the conventional 1 percent levels, respectively. This suggests that the lower the level of GDP per capita, the higher the growth effects of technology imitation (proxied by the share of imports in the "easy imitation" SITC category) relative to other forms of technology progress.

Table 2. Results of Panel System GMM Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
GDP ($t-1$)	-0.0597***	-0.0466**	-0.674***	-0.067**	-0.0477*	-0.0542*
	(-2.638)	(-2.320)		(-2.274)	(-1.666)	(-1.780)
Investment ratio	0.107***	0.185***	0.181***	0.164**	0.209***	0.174***
	(5.402)	(5.946)		(2.047)	(4.170)	(4.138)
Population growth	-0.331***	-0.253**	-0.482***	-0.394	-0.219	-0.291
	(-2.878)	(-2.065)		(-1.083)	(-1.568)	(-1.643)
Education	0.0669*	0.0583	0.0704*	0.064*	0.0531*	0.0723
	(1.755)	(0.0586)	(1.930)	(1.821)	(1.904)	(1.321)
Innovation	0.0624					
	(1.226)					
Imitation 1		0.0226*			1.143***	
		(1.801)			(4.064)	
Imitation 1($t-1$)			0.1065**			1.382***
			(2.571)			(4.069)
Imitation 2				0.0631		
				(1.268)		
Observations	758	758	709	706	492	486
			Specification tests			
Sargan/Hansen	0.353	0.21	0.405		0.575	0.764
Ar(2) Test, p-value	0.592	0.62	0.768		0.668	0.487

Notes: *significant at 10% level; ** significant at 5% level; *** significant at 1% level; t-values reported in parentheses; constant term and time dummies always included but not reported.
Ar(2) Test refers to the Arellano–Bond test for second-order correlation in differences, and Sargan/Hansen refers to the Sargan/Hansen test of overidentifying restrictions.

One thing that may not be entirely clear is why the innovation index (column 1) differs substantially from the estimates of the import coefficient from imitation (Columns 2–6). This may suggest that for technological progress to occur, African countries/firms are more dependent on imported inputs than on engaging in R&D activities of their own. Taken together, these findings corroborate the idea that developing countries initially reduce the technology gap through import-embedded technology and then proceed to other forms of imitation to achieve indigenous technological development (Jovanovic and MacDonald, 1994; Carolan et al., 1998). Overall, the findings of this study are consistent with endogenous growth theories, which consider “learning by importing” as an important channel of technological and economic growth. Learning via technology imitation could thus be one of the important underlying links between trade and growth. In addition, greater stocks of human capital are required insofar as imitating imported products requires some technical effort that the firm in the importing country did not previously have.

Lastly, the regressions may be subject to several methodological limitations, such as omitted variables, measurement errors, and sample selection. Appropriate empirical techniques should be adopted to address these issues. In addition, as data on trade statistics become available for more African countries, future research should allow sufficient time for the influence from changes in the input variables to affect the output variables.

6. Conclusion

This study aimed at assessing the effects of trade-induced technology imitation on economic growth in Africa, by using a production function approach in a panel system GMM estimator. The findings suggest that conditional on the level of the human capital index, economic growth tends to be greater in countries with higher ratios of technology imitation. Another noticeable finding is that the lower the level of GDP per capita, the higher the growth effects of technology imitation relative to other forms of technological progress. In a sense, the results support the view that certain forms of technology imitation (such as imported low-technology–intensive items) have a positive and significant effect on growth for the sample of African economies under study. In other words, and perhaps unsurprisingly, the link between trade and growth is a conditional one. That is, economic growth tends to be greater in countries with higher ratios of technology imitation, since technology imitation requires creative effort on the part of a firm’s employees and will consequently develop capabilities such as skills and efficiency.

Combining these results, we may conclude that importing of low-technology–intensive items for processing purposes has the potential for enhancing technological progress by providing domestic firms in Africa with access to technologies which are embodied in foreign capital goods that are not available domestically. Hence, African policymakers would do well to foster technological progress by focusing on tax incentives designed to encourage local firms to engage in imports of technology-intensive parts and components as inputs to their production processes.

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