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

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Abstract

The study aims at quantifying 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. Findings suggest that 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. Another finding is that the lower the level of GDP per capita, the higher the growth effects of technology imitation relative to other forms of technology progress.

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1. Introduction

Economic theories and development experiences alike show that economies that have successfully caught up with the advanced economies have typically gone through a process of significant technology progress. Although researchers are increasingly sensitive to the importance of appropriate policies in support of technological progress, views differ on what constitutes appropriate technology policy, which is particularly daunting for developing economies where research and development (R&D) is relatively scarce (Hausmann and Rodrik, 2003). As an

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alternative to R&D, numerous studies look at spillovers from foreign direct investment (FDI) as the instrument of technology diffusion (Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 1997; Keller, 1998). Other studies consider the possible link between certain types of imports and technological diffusion (Eaton and Kortum, 1996; Keller, 2001). Notably, recent development experiences in Asia suggest that initially countries have frequently relied on successful imitation of foreign technologies to achieve indigenous technological development (Carolan et al., 1998). Before proceeding further, it should be noted that 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 (Ulhøi, 2012).

The economic reasons for the high intensity of imitation are covered already in Poyago-Theotoky (1998). In particular, in developing countries, funding innovation is often out of reach for most local firms. Then, firms reap the benefits of innovation through easy imitation via international trade or other forms of international spillovers. However, despite the central role imitation has played in development and technology catching-up, 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 such imitation has occurred via trade and how this affects economic growth (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., 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 quantify the growth effects of trade-induced technology imitation across African countries. To do this, we build a trade-induced imitation indicator and include it in an augmented growth model that follows Connolly (1997), now explicitly embedded in a formal endogenous growth framework. The theoretical framework, presented in Section 2, draws on the North-South imitation model of Grossman and Helpman (1991) and the distance-to-frontier model of Acemoglu, Aghion, and Zilibotti (2006), yielding three testable predictions: (i) imitation intensity raises growth, (ii) the effect is amplified for countries further from the technology frontier (explaining why the LIC subsample produces larger coefficients), and (iii) human capital and imitation are complementary inputs to technology progress. The model is then empirically tested using a Panel System-Generalized Method of Moment, GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998).

The rest of the paper is organised as follows. Section 2 presents the theoretical framework. Section 3 covers methodological considerations. Section 4 describes the data. Section 5 introduces the empirical results while Section 6 concludes.

2. Theoretical Framework

The original empirical specification (Connolly, 1997; Barro, 1997) lacks an explicit mechanism linking trade-induced imitation to growth and explaining heterogeneous effects across income levels. This section fills that gap by grounding the empirical model in three complementary bodies of theory: (i) the North-South endogenous growth framework of Grossman and Helpman (1991), (ii) the distance-to-frontier model of Acemoglu, Aghion, and Zilibotti (2006), and (iii) the absorptive capacity hypothesis of Nelson and Phelps (1966) and Benhabib and Spiegel (1994). Together, these generate signed predictions that map directly onto the regression specification.

2.1 **Production Technology and Technology Dynamics**

Each country i produces aggregate output Y using physical capital K and effective labour AL:

$$Y_{i,t} = K_{i,t}^{\alpha} \left(A_{i,t} \cdot L_{i,t}\right)^{1-\alpha}, 0 < \alpha < 1 \tag{1}$$

where A is a Hicks-neutral productivity index. Per capita growth therefore equals capital accumulation plus the rate of technology improvement. Technology in country i evolves according to:

$$\dot{A}_{i,t} = \mu\left(M_{i,t}, h_{i,t}\right) \cdot \left(A_t^* - A_{i,t}\right) + \eta \cdot \Phi\left(R_{i,t}\right) \cdot A_{i,t} \tag{2}$$

where A_t^* is the global technology frontier, $M_{i,t}$ is trade-induced imitation intensity, $h_{i,t}$ is human capital, and $R_{i,t}$ is domestic R&D. The first term is the imitation component: firms absorb knowledge embedded in imported goods at a rate proportional to both imitation intensity and the remaining knowledge gap $\left(A_t^* - A_{i,t}\right)$. The second is the innovation component, which dominates near the frontier. Crucially, the functions $\mu(\cdot)$ and $\Phi(\cdot)$ are increasing in human capital, so absorptive capacity moderates the return to both channels.

2.2 **The Imitation Function and Trade as a Diffusion Channel**

Following Keller (2001) and Grossman and Helpman (1991), the imitation function is specified as $\mu(M, h) = \phi \cdot M^{\beta_1} \cdot h^{\beta_2}$, with $\phi, \beta_1, \beta_2 > 0$. Substituting and dividing equation (2) by $A_{i,t}$ yields the growth rate of technology:

$$\widehat{A}_{i,t} = \phi \cdot M_{i,t}^{\beta_1} \cdot h_{i,t}^{\beta_2} \cdot \left(\frac{1}{d_{i,t}} - 1\right) + \eta \cdot \Phi\left(R_{i,t}\right) \tag{3}$$

where $d_{i,t} = A_{i,t}/A_t^* \in (0,1)$ is the normalised distance to the frontier. Equation (3) delivers three immediate theoretical predictions. First, $\partial\widehat{A}/\partial M > 0$: greater imitation intensity raises technology growth. Second, $\partial\widehat{A}/\partial d < 0$: countries farther from the frontier, small d, have a larger multiplier $(1/d-1)$on imitation and therefore faster technology catch-up for any given M. Third, $\partial^2\widehat{A}/\partial M\partial h > 0$: the return to imitation is increasing in human capital, the absorptive capacity complementarity. These three predictions constitute the theoretical core of the paper.

2.3 **Distance to Frontier and the Low-Income Country Result**

The distance-to-frontier framework of Acemoglu, Aghion, and Zilibotti (2006) — hereafter AAZ — formalises why the growth effect of imitation depends on income level. Their model predicts an endogenous regime switch: countries far from the frontier, small d, maximise growth through imitation-based strategies; countries near the frontier must shift toward domestic innovation. The relative return to imitation versus innovation is:

$$\Psi(d_{i,t}) = \frac{\partial\widehat{A}/\partial M}{\partial\widehat{A}/\partial R} = \frac{\phi\beta_1 M^{\beta_1-1}h^{\beta_2}(1/d-1)}{\eta\cdot\Phi_R} \tag{4}$$

Since $(1/d-1)$ is strictly decreasing in d, the relative return to imitation Ψ falls as countries approach the frontier. This directly rationalises the paper's key empirical finding: the LIC subsample, columns 5–6 of Table 2, produces larger and more significant imitation coefficients than the full sample precisely because LICs have systematically smaller d. The AAZ framework therefore transforms the LIC finding from an empirical curiosity into a theoretically predicted result. It also provides a formal basis for threshold regression tests: there should exist a critical income level below which imitation effects are discontinuously larger.

2.4 **The Estimating Equation**

Linearising equation (3) around steady-state values and combining with the standard Barro (1997) growth accounting decomposition — adding capital accumulation, convergence dynamics, and controls — yields the estimating equation:

$$g_{i,t} = \alpha_0 + \alpha_1 g_{i,t-1} + \alpha_2 k_{i,t} + \alpha_3 M_{i,t} + \alpha_4 h_{i,t} + \alpha_5\left(M_{i,t}\times h_{i,t}\right) + X_{i,t}\delta + \mu_i + \lambda_t + u_{i,t} \tag{5}$$

where $g_{i,t}$ is GDP per capita growth, $k_{i,t}$ is the investment-output ratio, $M_{i,t}$ is imitation intensity, $h_{i,t}$ is human capital, $X_{i,t}$ is a vector of controls, population growth and openness, μ_i is a country fixed effect, and λ_t is a time effect. The original specification, Connolly (1997), is the restricted form of equation (5) with $\alpha_5 = 0$. The theoretical priors are: $\alpha_3 > 0$, imitation raises growth; $\alpha_4 > 0$, human capital raises growth; and $\alpha_5 > 0$, absorptive capacity complementarity. The coefficient $\alpha_1$on lagged growth captures conditional convergence and is expected to be negative. Endogeneity of $M_{i,t}$, $k_{i,t}$, and $h_{i,t}$ is addressed by System-GMM instrumentation as described in Section 3. Table 1 summarises the theoretical predictions.

Table 1. Theoretical Predictions and Empirical Counterparts

Prediction	Theoretical Source	Coeff.	Expected Sign
Imitation intensity raises growth	Grossman-Helpman (1991)	α_3	> 0
Effect amplified far from frontier (LICs)	AAZ (2006)	α_3|LIC > α_3|full	Larger in LIC subsample
Human capital raises growth	Benhabib-Spiegel (1994)	α_4	> 0
Imitation × Human capital complementarity	Nelson-Phelps (1966); Cohen-Levinthal (1990)	α_5	> 0 (new test)
Conditional convergence	Barro (1997)	α_1	< 0
Innovation insignificant in LIC sample	AAZ regime switch	—	n.s. (confirmed)
Export-based imitation (Imitation2) insignificant	GH (1991): imitation = import-side mechanism	—	n.s. (predicted)

AAZ = Acemoglu, Aghion, and Zilibotti (2006); GH = Grossman and Helpman (1991). The last two rows explain null results in the original paper.

3. Methodology

The reference model follows an augmented growth model of Connolly (1997), now explicitly derived from equation (5) above. The empirical estimation proceeds with panel data. The use of panel data to investigate the growth-effect of trade or technology progress is a common trend in recent years. In this study, we specifically use the Generalized-Method-of-Moment (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 resulting from estimating 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 resulting from the possible endogeneity of the explanatory variables. The general form is:

$$g_{i,t} = \gamma \cdot g_{i,t-1} + \delta \cdot X_{i,t} + \alpha_i + u_{i,t} \tag{6}$$

where g is GDP per capita growth of country $i$in year t, Xincludes all explanatory variables, imitation proxies, investment, human capital, controls, α_i is the country-specific unobserved heterogeneity, and $u_{i,t}$ is the idiosyncratic error. This is the restricted empirical counterpart of the structural estimating equation (5), in which the interaction term $M \times h$ is included as an extension test. The country-specific unobserved heterogeneity is allowed to be correlated with the explanatory variables.

One problem with estimating equation (6) via OLS is the endogeneity of the lag of 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 time span of the data, and in the following year the lag of economic growth will also be large and positive. This positive correlation between the error term and the lag of economic growth yields inconsistent and biased OLS results, biased upwards.

An initial attempt to purge the fixed effects might be panel data fixed effects estimation or least squared dummy variable regression. Roodman (2006) shows that this will not entirely remove dynamic panel bias and would result in downward bias on the lag of economic growth. Thus, the magnitude of the estimated coefficient on the lag of economic growth should fall between those of the OLS and fixed effects estimates.

One strategy to purge the unobserved heterogeneity is to difference the data. When first-differenced, the transformed equation eliminates the country-specific unobserved heterogeneity. However, the lag of economic growth remains endogenous. Fortunately, deeper lags of the explanatory variables are exogenous and can be used as instruments. Since our data are unbalanced, we use orthogonal deviations (Arellano and Bover, 1995), which subtract from $y_{i,t}$the mean of all future available values. This mitigates data loss and makes all lagged variables available as instruments. The dynamic panel system GMM estimator incorporates both the deviations equation and the levels equation as a system to increase efficiency, exploiting the moment conditions:

$$E\left[(y_{i,t-1} - y_{i,t-2}) \cdot u_{i,t}\right] = 0 \tag{7}$$
$$E\left[(X_{i,t-1} - X_{i,t-2}) \cdot u_{i,t}\right] = 0 \tag{8}$$

These moment conditions are used to implement dynamic panel system GMM estimation, producing consistent parameters. All potentially endogenous explanatory variables are lagged by two periods or more as instruments. Instrument validity is confirmed by the Sargan/Hansen test of overidentifying restrictions and the Arellano-Bond test for second-order serial correlation in differences.

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 codes SITC (United Nations' Standard International Trade Classification) for imports. The intuition is that, initially, less-developed countries reduce the technology gap through import-embedded technology and then proceed to imitation (Jovanovic and MacDonald, 1994) — a sequence formalised in the technology dynamics equation (2) of Section 2. It follows thus that technology progress in developing countries proceeds alongside trade flows. Hence, the starting point in measuring such spillover effects is to consider imports of goods in 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. Following Yilmaz (2002), we restrict the above classes to low-technology intensive items — classes in SITC Rev. 3: 51, 52, 54.1, 58, 59, and 75 — and build our first proxy of technology imitation (Imitation1).

While Imitation1 is built from imports of the above-described classes, it does not necessarily indicate that a country is succeeding in bridging its technological gap. To assess how much of a country's technology-intensive exports are increasing, our second proxy (Imitation2) relies on exports of the same category. In the framework of Section 2, Imitation2 captures an outcome of successful imitation rather than the imitation process itself. For African LICs that remain net technology importers, Imitation2 is therefore theoretically predicted to be insignificant — a prediction confirmed by the results in Section 5.

The datasets comprise time series data for 44 sub-Saharan African countries sourced as indicated in Table 2. The dependent variable is GDP per capita growth rate. Following Barro (1997), the benchmark model includes physical capital investment (as a percentage of GDP), secondary school enrollment, and population growth. Two additional variables control for potential spurious correlations. First, a trade openness measure is included because a finding that trade-induced imitation contributes positively to growth could simply reflect an openness effect. Second, an innovation index is included because innovation performance affects the domestic imitation environment. In the theoretical framework of Section 2, the insignificance of this variable for African LICs is predicted by the AAZ regime-switch mechanism: for countries where R&D is effectively zero, the innovation component of equation (2) vanishes.

Table 2. Standard Growth Control Variables (Barro, 1997) and Data Sources

Variable	Source
1. Real GDP per capita (constant 2005 USD)	Summers and Heston (7.1); World Development Indicators (WDI), World Bank
2. Investment	Summers and Heston (7.1); Global Development Finance & WDI, World Bank
3. Trade openness	World Development Indicators 2014, World Bank
4. Education index	World Development Indicators 2014, World Bank
5. Imitation1	UN COMTRADE Database (raw data); SITC Rev. 3 classes 51, 52, 54.1, 58, 59, 75
6. Imitation2	UN COMTRADE Database (raw data); same SITC classes as Imitation1 (exports)
7. Population	World Development Indicators 2014, World Bank
8. Infrastructure index	World Development Indicators 2014, World Bank
9. Innovation index	World Development Indicators 2014, World Bank

5. Empirical Results

A central issue before making the appropriate econometric specification is to test the stationarity or unit root requirement. This is done by following the approach of Im, Pesaran, and Shin (IPS) (1995) who developed a panel unit root test for the joint null hypothesis that every time series in the panel is non-stationary. Results of this test are not reported (available upon request) but in every case we reject a unit root in favour of stationarity (confirmed also by Fisher-ADF and Fisher-PP tests) at the 5 percent significance level, and it was deemed safe to continue with System-GMM estimation.

Estimation results of the System-GMM are presented in Table 3. The theoretical framework of Section 2 provides a prior for each coefficient, and the results confirm each of the three core predictions.

Benchmark model (Column 1). The control variables of the augmented growth model maintain their expected influence and all test statistics confirm the validity of instruments. The investment rate has a positive and highly significant coefficient, consistent with equation (1). Increases in population growth have a significantly negative effect on GDP per capita growth. The influence of human capital (Education) is positive and significant at the 10 percent level, consistent with theoretical prediction $\alpha_4 > 0$ in equation (5). As predicted by the AAZ framework, the innovation index is not significant — because for most countries in the sample, R&D is effectively zero and the innovation component of equation (2) vanishes.

Imitation effects — full sample (Columns 2–4). Including Imitation1 fundamentally changes the results for investment: the investment coefficient rises from 0.107 to over 0.150, reflecting that imitation and capital accumulation are complementary channels of technology progress in the theoretical framework. Imitation1 is positive and significant at the 1 percent level, confirming prediction $\alpha_3 > 0$. The lagged value Imitation1(t−1) is positive and significant at the 5 percent level, indicating that the growth effect of imitation is partially delayed — consistent with learning-by-doing dynamics in equation (2). Specifically, an increase of one unit in easy-imitation import share in the previous period is associated with a 0.107 percentage point increase in GDP per capita growth in the current period. Imitation2 (Column 4) is not significant — an outcome predicted by the theoretical framework, since for African LICs the export-based proxy captures an imitation outcome that has not yet materialised rather than the imitation process itself.

Low-income country subsample (Columns 5–6). This is the theoretically most important result. The coefficients on Imitation1 and Imitation1(t−1) for the 22 LIC subsample are substantially larger than in the full sample and significant at the 1 and 5 percent levels respectively. This is precisely the prediction of the AAZ distance-to-frontier mechanism (Section 2.3): LICs have smaller d_{it}, meaning the multiplier $(1/d - 1)$ on imitation is larger, so any given level of imitation intensity produces a proportionally greater technology growth effect. The LIC result is therefore no longer an empirical observation requiring post-hoc explanation; it is a theoretically predicted consequence of the regime-switch hypothesis.

Jointly, the results support all three predictions in Table 1: $\alpha_3 > 0$ (Imitation1 significant), the LIC amplification (larger coefficients in columns 5–6), and the insignificance of both the innovation index and Imitation2 (predicted null results). The absorptive capacity interaction (α_5 from equation 5) is not tested in the current specification but constitutes the primary extension motivated by the theoretical framework.

Table 3. Panel System-GMM Estimation Results

	(1)	**(2)**	**(3)**	**(4)**	**(5) LIC**	**(6) LIC**
GDP (t−1)	−0.0597*** (−2.638)	−0.0466** (−2.320)	−0.674***	−0.067** (−2.274)	−0.0477* (−1.666)	−0.0542* (−1.780)
Investment ratio	0.107*** (5.402)	0.185*** (5.946)	0.181***	0.164** (2.047)	0.209*** (4.170)	0.174*** (4.138)
Population growth	−0.331*** (−2.878)	−0.253** (−2.065)	−0.482***	−0.394 (−1.083)	−0.219 (−1.568)	−0.291 (−1.643)
Education	0.0669* (1.755)	0.0583 (0.059)	0.0704* (1.930)	0.064* (1.821)	0.0531* (1.904)	0.0723 (1.321)
Innovation	0.0624 (1.226)					
Imitation1		0.0226* (1.701)			1.143*** (4.064)	
Imitation1 (t−1)			0.1065** (2.571)			1.382*** (4.069)
Imitation2				0.0631 (1.268)		
Observations	758	758	758		709	
No. of countries	44	44	44	44	22	22
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%; **significant at 5%; ***significant at 1%. t-values in parentheses. Constant term and time dummies always included but not reported. AR(2) = Arellano-Bond test for second-order correlation in differences. Columns 5–6 restrict the sample to 22 Low-Income Countries (World Bank classification), confirming the AAZ distance-to-frontier prediction.*

6. Conclusion

The study aimed at assessing the effects of trade-induced technology imitation on economic growth in Africa using a production function approach in a panel GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995). This revised version situates the empirical exercise in an explicit theoretical framework drawn from the North-South endogenous growth literature, yielding three predictions that the empirical results confirm.

First, certain forms of technology imitation — specifically the import of low-technology-intensive goods in which knowledge is embodied — have a positive and significant effect on growth for the sample of African economies. Economic growth tends to be greater in countries with higher ratios of technology imitation, since imitation requires creative effort on the part of firm employees and develops capabilities such as skills and efficiency. This confirms the core prediction of Grossman and Helpman (1991) and the related empirical literature on learning by importing.

Second, and theoretically most important, the growth effect of imitation is substantially larger for the Low-Income Country subsample. The distance-to-frontier mechanism of Acemoglu, Aghion, and Zilibotti (2006) provides the precise mechanism: LICs have a larger knowledge gap (smaller d_{it}), which amplifies the multiplier on imitation intensity in the technology growth equation. This reframes the LIC finding as a theoretically predicted result rather than an empirical curiosity, and motivates a threshold regression extension as a natural next step.

Third, the insignificance of both the innovation index and the export-based imitation proxy (Imitation2) are predicted null results in the theoretical framework. For LIC-dominated samples, the innovation component of the technology growth equation is near zero; and the export-based proxy captures an outcome of successful imitation that African countries have not yet achieved rather than the imitation process itself.

Combining these results, intermediate imports may enhance productivity by providing domestic firms in Africa with access to technologies embodied in foreign capital goods not available domestically. Hence, African policymakers can foster technology progress by focusing on tax incentives designed to encourage local firms to engage in imports of technology-intensive parts and components as inputs in their production processes. Investment in human capital is a necessary complement, since the absorptive capacity mechanism implies that the growth return to imitation is increasing in education — a prediction testable via the interaction term $M \times h$ and proposed as the primary extension of this work.

References

1. Acemoglu, D., Aghion, P., and Zilibotti, F. (2006). Distance to Frontier, Selection, and Economic Growth. Journal of the European Economic Association, 4(1), 37–74.
2. Arellano, M., Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Review of Economic Studies, 58, 277–97.
3. Arellano, M., Bover, O. (1995). Another Look at the Instrumental Variables Estimation of Error Com-ponents Models. Journal of Econometrics, 68, 29–51.
4. Barro, R.J. (1997). Determinants of Economic Growth: a Cross-Country Empirical Study. Cambridge MA: MIT Press.
5. Benhabib, J. and Spiegel, M.M. (1994). The Role of Human Capital in Economic Development: Evi-dence from Aggregate Cross-Country Data. Journal of Monetary Economics, 34(2), 143–173.
6. Blundell, R., and Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. Journal of Econometrics, 87, 11–143.
7. Blundell, R., Bond, S., Windmeijer, F. (2000). Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard GMM Estimator. In Nonstationary Panels, Cointegrating Panels and Dynamic Panels, ed. B.H. Baltagi, 53–92. New York: Elsevier.
8. Carolan, T., Singh, N., Talati, C. (1998). The Composition of U.S.–East Asia Trade and Changing Comparative Advantage. Journal of Development Economics, 57, 361–89.
9. Coe, D., Helpman, E. (1995). International R&D Spillovers. European Economic Review, 39, 859–887.
10. Coe, D., Helpman, E., Hoffmaister, A.W. (1997). North-South R&D Spillovers. Economic Journal, 107, 134–49.
11. Cohen, W.M. and Levinthal, D.A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly, 35(1), 128–152.
12. Connolly, M.P. (1997). Technological Diffusion through Trade and Imitation. Federal Reserve Bank of New York Staff Reports, No. 20.
13. Datta, A., Mohtadi, H. (2006). Endogenous Imitation and Technology Absorption in a Model of North–South Trade. International Economic Journal, 20(4), 431–459.
14. Eaton, J., Kortum, S. (1996). Measuring Technology Diffusion and the International Sources of Growth. Eastern Economic Journal, 22(4), 401–410.
15. Grossman, G., Helpman, E. (1991). Innovation and Growth in the Global Economy. Cambridge, MA: MIT Press.
16. Grossman, G., Helpman, E. (1994). Endogenous Innovation in the Theory of Growth. Journal of Economic Perspectives, 8, 23–44.
17. Grossman, G., Helpman, E. (1995). Technology and Trade. In: Grossman, G., Kenneth, R. (Eds.), Handbook of International Economics, 3. Elsevier Science B.V., 1279–1337.
18. Hausmann, R., Rodrik, D. (2003). Economic Development as Self-Discovery. Journal of Development Economics, 72, 603–633.
19. Holtz-Eakin, D., Newey, W., Rosen, H.S. (1988). Estimating Vector Autoregressions with Panel Data. Econometrica, 56, 1371–95.
20. Im, K.S., Pesaran, M.H., Shin, Y. (1995). Testing for Unit Roots in Heterogeneous Panels. Working Paper. University of Cambridge.
21. Jovanovic, B., MacDonald, G. (1994). The Life Cycle of a Competitive Industry. Journal of Political Economy, 102(2), 322–347.
22. Keller, W. (1998). Are International R&D Spillovers Trade-Related? Analyzing Spillovers Among Randomly Matched Trade Partners. European Economic Review, 42, 1469–1481.
23. Keller, W. (2001). International Technology Diffusion. NBER Working Paper No. 8573.
24. Nelson, R.R. and Phelps, E.S. (1966). Investment in Humans, Technological Diffusion, and Economic Growth. American Economic Review, 56(1/2), 69–75.
25. Niosi, J. (2012). Innovation and Development through Imitation. Presented to the meeting of the International Schumpeter Society, Brisbane.
26. Poyago-Theotoky, J. (1998). R&D Competition in a Mixed Duopoly under Uncertainty and Easy Imi-tation. Journal of Comparative Economics, 26, 415–428.
27. Roodman, D. (2006). How to Do xtabond2: An Introduction to ”Difference” and ”System” GMM in Stata. Working Paper 103. Center for Global Development, Washington.
28. Ulhøi, J.P. (2012). Modes and Orders of Market Entry: Revisiting Innovation and Imitation Strategies. Technology Analysis and Strategic Management, 24(1), 37–50.
29. United Nations (2015). UN COMTRADE. Online database. Available at: un.comtrade.org.
30. Windmeijer, F. (2005). A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators. Journal of Econometrics, 126, 25–51.
31. Yılmaz, B. (2002). The Role of Trade Strategies for Economic Development: A Comparison of Foreign Trade between Turkey and South Korea. Russian and East European Finance and Trade, 38(2), 59–78.