*Economic Issues, Vol. 25, Part 1, 2020*

# Domestic industrial learning externalities of innovation and imitation: Informing industrial policy with Cross-country evidence

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Abstract

*This study estimates four different domestic industrial learning externalities of and between imitation and innovation. Using highly disaggregated industrial data as measures for product varieties, we test for the relationship between imitation and innovation based on four theoretically informed, policy-relevant hypotheses. In sum, we document robust and statistically significant* stepping-stone *effect of imitation on innovation, and a reverse positive* creative-imitation *effect from innovation to imitation. Likewise, we also estimate positive within-sector learning effects for both innovation and imitation. These empirical findings have significant implications for industrial policies designed to foster innovation-driven growth, especially in middle-income and developing economies.*

*JEL Classification: O11, O40, O47*
*Keywords: Industrialisation, Industrial Policies, Imitation, Innovation*

## 1. Introduction

At the nascent stage of economic development, many well-intended policymakers in emerging economies understood how to go about designing an effective industrial policy, which can be broadly classified into import-substituting industrialisation, export-oriented industrialisation, resource-based industrialisation, and export processing zones (Low and Tijaja 2013). By promoting both domestic and inward foreign investments, as well as improving the overall climate for doing business, many developing economies managed to position themselves at the lower end of global production value chains and, consequently, develop an industrial base characterised primarily by labour-intensive, low value-added manufacturing based on imitated foreign technology. Over the past 60 years, the successful implementation of such an industrialisation strategy has contributed to many developing economies growing quickly out of poverty to attain middle-income status.

However, having achieved middle-income status, policymakers then find it much harder to push the economy into high-income status based on their previous strategy. Over the period 1960-2018, only 16 out of 182 economies have successfully attained high-income status (Cherif and Hasanov 2019). Indeed, most emerging economies, including previous high performers such as Malaysia (Zeufack and Lim 2013), have faced problems with sustaining the competitiveness of their manufacturing industries.[2] With most emerging economies expected to enter a decade of moderate external demand, growth must therefore *increasingly spring from knowledge, innovation, and a deeper stock of physical and human capital* domestically, by promoting firms *to learn to do new things—venturing into unfamiliar export industries for example—and to do things in new ways.* (Commission on Growth and Development 2008). In short, developing-economy policymakers ought to promote domestic industrial transformation through industrial upgrading from imitation-reliance to indigenous innovation-driven.

While the broad direction of increasingly domestically-driven industrial policies is clear, there is a knowledge gap in terms of understanding the precise mechanisms (and their respective magnitudes) affecting industrial transformation. For instance, South Korea and Taiwan are two economies with very different industrial strategies [the former dominated by large Chaebols and the latter driven by small and medium enterprises (SMEs)], which suggest vastly different industrial dynamics. Similarly, between the neighbouring Singapore and Malaysia, the former built an industry dominated by multinationals operating at the technological frontier (hence, growing via expansion of innovation varieties), whereas the latter is driven by large government-linked companies, which serve as industrial innovation leaders that inspire imitation activities for the rest of the firms.[3] In Chandra *et al* (2012), these various learning-by-doing channels in the manufacturing industries are identified as being driven by the dynamics of imitation and innovation variety expansion, à la Romer (1990), as well as their mutual interaction effects, dating back even to the Industrial Revolution era. Indeed, to reap the benefits from learning-by-doing and knowledge spillovers within and between industries would necessitate the implementation of strategic industrial policies (Harrison and Rodriguez-Clare 2010; Günther and Alcorta 2011), hence reaffirming the endogeneity of these issues: accurate estimates of the learning effects within and between innovation and imitation are key to informing effective industrial policy design, but good industrial policy would promote these learning effects.

The main purpose of this study is to model and estimate these different learning-by-doing mechanisms. On a macro, aggregate level, we identify **four** endogenous knowledge externality channels that are of industrial policy significance. First, knowledge can be acquired and grow by producing new products, be it from adopting the standardised processes of foreign products (*imitation growth*) or from new products developed domestically (*innovation growth*). Both of these are termed *standing-on-shoulder* effects (Caballero and Jaffe 1993; Jones 2005), and characterised the industrial growth experience described for South Korea. Further, firms that started off as imitators of foreign processes can eventually undergo an upgrade in technological capability, and then transit to developing new product varieties. This learning mechanism that goes from imitation to innovation is known as the *stepping-stone* effect (Glass 1999; Collins 2015). This corresponds to the industrial learning experience of Taiwan, which started off with a network of SMEs, some of which eventually progressed to become global frontier innovators in their respective industries. Lastly, consistent with the described Malaysian experience, a fourth spillover mechanism can take place from innovation to imitation activities, seen in studies such as Mukoyama (2003) and Lim (2019). Knowledge of the significance of these industrial spillover externalities, notably econometric estimation of the magnitudes of these learning-by-doing mechanisms, would contribute towards better understanding of industrial policies in developing economies, as well as informing their significance in driving the various stages of development of developing economies (Funke and Strulik 2000; Agénor and Dinh 2013). For examples, if the *stepping-stone* effect is insignificant, do policymakers in up-and-coming countries, such as the East African Community economies, still follow the standard prescription of export-oriented industrialisation? Likewise, if the *standing-on-shoulder* effects is weak for the innovation sector, does that mean the offshoring and technological migration activities by multinationals do more harm than good by destabilising domestic industrial development? These are pertinent questions for industrial policies, and will inform the respective roles of innovation and imitation in driving the various stages of development in developing economies (Funke and Strulik 2000; Agénor and Dinh 2013). Despite the significance to industrial policy design globally, based on our knowledge, to date, there is no cross-country study that estimates these different learning mechanisms jointly.[4]

To preview, using the highly disaggregated industrial data INDSTAT 4, released by the United Nations Industrial Development Organisation (UNIDO), this study is the first to establish empirically the presence of a positive *stepping-stone* effect across countries. Further, by estimating a positive effect of innovative variety on the expansion of imitative varieties, we also find empirical evidence in support of a complementary relationship between innovative and imitative industrial varieties. These are significant for the design of industrial policies as they suggest that the development of both imitative and innovative variety-based industries is important, irrespective of the development stage an economy is in. This is in contrast to a usual misconception that middle-income economies ought to seek out only the firms that are in the technological frontier when designing their industrial and FDI strategies.

The rest of the article is structured as follows. In Section 2, the key features of our theoretical model are described and summarised (see Appendix A for more formal and elaborative presentation of the model). Section 3 derives an estimatable empirical structure for the theoretical model. This is then followed by Section 4, which discusses the empirical strategy and the estimation results. Section 5 concludes by discussing further policy implications.

## 2. Theoretical Model

### 2.1 Households

To provide a theoretical basis to our empirical estimation, we develop a theoretical model describing industrial transformation in the form of expanded varieties, based on Agénor and Dinh (2013) and Lim (2019). The model economy is populated by individuals with identical preferences but different innate abilities, who live for two periods. Population is constant at $\bar{N}$. Abilities, $a \in (0, 1)$, are instantly observable and assumed to be uniformly distributed. At the beginning of adulthood, individuals choose whether to spend a fraction $\varepsilon \in (0, 1)$ and training cost, $tc_t$, to undergo training. This decision determines the proportion of skilled and unskilled workers. It is optimal for an individual with ability $a_t \in (a_m, 1)$ to train and become skilled if and only if their life-long indirect utility of being skilled ($V_t^S$) outweighs that of being unskilled ($V_t^U$), with the indirect utility function given by

$$V_t^h = \ln c_t^{h,t} + \frac{\ln c_{t+1}^{h,t}}{1+\rho}, \quad h = U, S, \quad j = 0, 1 \tag{1}$$

As shown in Appendix A, a theoretical threshold ability, $a_t^C$, above which individuals choose to remain unskilled can be derived, which is then used to determine the proportion of unskilled, $\theta_t^U$, and effective skilled labour, $\theta_t^S$. This theoretical specification is consistent with cross-country evidence, where innovation tends to correlate with the expansion of skilled workers via enhanced education quality (Hanushek and Kimko 2000; Vandenbussche *et al* 2006; Maloney and Rodriquez-Clare 2007).

### 2.2 Production

First, there is a final good sector populated by a continuum of perfectly competitive, profit-maximising firms. These firms employ $\chi N_t^U$ unskilled labour in the economy. For each firm, production uses untrained labour, private capital ($K_t^P$), and a composite intermediate input which, in a symmetric equilibrium, is written as

$$X_t = [(M_t^I)^{1/\eta} x_t^I]^{\upsilon} [(M_t^R)^{1/\eta} x_t^R]^{1-\upsilon} \tag{2}$$

where $\int_0^{M_t^I} (x_{s,t}^I)^\eta ds = M_t^I (x_t^I)^\eta$ and $\int_0^{M_t^R} (x_{s,t}^R)^\eta ds = M_t^R (x_t^R)^\eta$. These reflect the aggregate innovative varieties ($M_t^R$), imitative varieties ($M_t^I$), and the respective quantity of intermediate goods (IGs), $x_{i,s,t}$, with $s \in (0, M_t)$. As shown in Appendix A, after solving for the first-order conditions, and upon imposing certain theoretical restrictions on the congestion parameters, we can write the aggregate output of the economy in the standard AK-form of $Y_t = f(m_t^R, m_t^I; \tilde{k}^G) K_t^P$. This expresses the final good as a function of effective innovative varieties ($m_t^R$), effective imitative varieties ($m_t^I$), and an exogenously-given level of effective public infrastructure stock ($\tilde{k}^G$), where $m_t^R = M_t^R / K_t^P$, $m_t^I = M_t^I / K_t^P$, $\tilde{k}^G = \tilde{K}^G / K_t^P$. By definition, this specification is consistent with industrial policies in developing economies, where the government plays a direct role in influencing industrial activities. The capital-intensive specification for variables is also consistent with the long-term growth experience observed worldwide for developing economies.

The final good sector is supported by two different but symmetric production structures, modelled in similar fashion to Gustafsson and Segerstrom (2010). Specifically, there are two sets of monopolistically-competitive IG producers: those producing imitation-based inputs using blueprints from the imitation sector, and those producing innovation-based inputs, based on blueprints from the innovation sector.

The blueprints are produced in two sectors: an innovative sector, which employs skilled labour, in quantity $N_t^S$, to produce variety, $M_t^R$, and an imitation sector, which employs a constant share of unskilled labour, $(1-\chi)N_t^U$ to produce variety, $M_t^I$. The aggregate technology in the imitation sector is defined as

$$M_{t+1}^I - M_t^I = A_t^I\left(\frac{(1-\chi)N_t^U}{N_t}\right) \tag{3}$$

where $A_t^I = A(M_t^I;\, M_t^R;\, \tilde{k}^G)$ is a productivity parameter determining the degree of knowledge spillover. To capture the policy context of our model, this specification includes a direct learning effect from stock of imitation ($M_t^I$) documented empirically by Ang and Madsen (2015a), and the spillover effect from innovation ($M_t^R$), as in Lim (2019). In addition, as in Agénor and Neanidis (2015), a positive productivity effect from access to public capital ($\tilde{k}^G$) is also specified. Profit maximisation by imitative firms yields the first-order condition for the unskilled wage, $w_t^U$.

On the other hand, the aggregate technology in the innovation sector is defined as

$$M_{t+1}^R - M_t^R = A_t^R\left(\frac{(1-\varepsilon)N_t^S}{N_t}\right) \tag{4}$$

where $A_t^R = A(M_t^R;\, M_t^I;\, \tilde{k}^G)$ is the corresponding productivity parameter, which depends again on the direct learning effect from the existing stock of innovative variety, the *stepping-stone effect* discussed in the *Introduction* (Glass 1999; Collins 2015), and the effective public capital stock. Given that skilled labour is employed in innovation, profit maximisation by innovative firms yields the first-order condition for skilled wage, $w_t^S$.

*2.3 Government and Market-Clearing Conditions*

The government taxes only wages. A constant fraction of government revenue is spent on public capital investment, $G_t^I$, and the remaining on all other non-productive spending, $G_t^O$. It is assumed that the government cannot borrow. Specifically,

$$G_t = \sum G_t^h = \upsilon_h \tau\{w_t^U N_t^U + [(1-\varepsilon)w_t^S - tc_t]N_t^S\},\ h = I, O \tag{5}$$

where $\upsilon_h \in (0, 1)$, $\sum_i \upsilon_i = 1$.

Both the skilled and unskilled labour markets clear. The saving-investment balance also holds for the private capital stock.

## 3. Empirical form and hypothesis formulation

The *dynamic* and *balanced growth equilibriums* of the model are defined in Appendix A, which are followed by analytical solutions. The dynamic form of the solution can be condensed into a 2x2 first-order linear difference equation system in log-deviations from the steady state, $\hat{m}_t^R = \ln m_t^R$ and $\hat{m}_t^I = \ln m_t^I$, where

$$\begin{bmatrix} \hat{m}_{t+1}^R \\ \hat{m}_{t+1}^I \end{bmatrix} = \begin{bmatrix} \Omega_R^1 & \Omega_I^1 \\ \Omega_R^2 & \Omega_I^2 \end{bmatrix} \begin{bmatrix} \hat{m}_t^R \\ \hat{m}_t^I \end{bmatrix} \tag{6}$$

$\Omega_R^1$ and $\Omega_I^2$ are interpretable as the respective aggregate *standing-on-shoulder* effects, $\Omega_1^I$ the *stepping-stone effect*, and $\Omega_R^2$ the spillover effect from innovation to imitation, dubbed *creative imitation* effects. With $Y_t$ and $K_t^P$ growing at the same rate along the balanced growth path, we can then write the long-run growth rate as depending on the imitative varieties, the innovative varieties, and public capital. As motivated in the *Introduction*, the coefficients represent **four** key knowledge spillover channels of significance in the context of industrial policy. For **endogeneity** considerations, these spillover channels are estimated jointly in the empirical analysis, with the benchmark empirical setup represented by:

$$\begin{aligned} innov_{jt} = {} & \alpha_0 + \alpha_1 innov_{jt-1} + \alpha_2 imit_{jt} + \alpha_3 imit_{jt-1} + \alpha_4 pubcap_{jt} \\ & + \alpha_5 initGDP_{jt} + \sum_{l=1}^{L} \psi_l X_{l,jt} + \sum_{m=1}^{n-1} \lambda_m Z_{m,jt} + \mu_{jt} + u_{jt} \end{aligned} \tag{7}$$

$$\begin{aligned} imit_{jt} = {} & \beta_0 + \beta_1 innov_{jt} + \beta_2 imit_{jt-1} + \beta_3 imit_{jt-1} + \beta_4 pubcap_{jt} \\ & + \beta_5 initGDP_{jt} + \sum_{l=1}^{L} \psi_l X_{l,jt} + \sum_{m=1}^{n-1} \lambda_m Z_{m,jt} + \mu_{jt} + v_{jt} \end{aligned} \tag{8}$$

$$pubcap_{j,t} = \gamma_0 + \gamma_1 urban_{jt} + \gamma_2 popdens_{jt} + \sum_{m=1}^{n-1} \lambda_m Z_{m,jt} + \mu_{jt} + z_{jt} \tag{9}$$

$$\begin{aligned} g_{j,t} = {} & \delta_0 + \delta_1 initGDP_{jt} + \delta_2 innov_{jt} + \delta_3 imit_{jt} + \delta_4 pubcap_{jt} \\ & + \delta_5 \Delta innov_{jt} + \delta_6 \Delta imit_{jt} + \sum_{k=1}^{K} \xi_k \Upsilon_{k,jt} + \mu_{jt} + \varepsilon_{jt} \end{aligned} \tag{10}$$

where $j(t)$ is a country (time) index; $innov_{jt}$ and $imit_{jt}$ are innovative and imitative varieties; $pubcap_{j,t}$ is public capital stock; $g_{j,t}$ is growth rate of per capita real GDP; $initGDP_{jt}$ is the logarithm of initial per capita GDP (introduced to capture the conditional convergence effects). In line with Agénor and Neanidis (2015), we also examine the contemporaneous effects between the two main endogenous variables, introduce urban shares and population density in the equation for public capital stock, and use $\{Z_{m,jt}\}_{m=1}^{n-1}$, a set of fiscal variables in levels (measured as fractions of GDP) for exclusion restriction, with the excluded factor being tax revenue. $\{X_{l,jt}\}_{l=1}^{L}$ and $\{\Upsilon_{k,jt}\}_{k=1}^{K}$ denote the set of control variables for the industrial knowledge production functions and economic growth. Lastly, $\mu_{jt}$ captures time-invariant country-specific effects, whereas $u_{jt}$, $v_{jt}$, $z_{jt}$ $\varepsilon_{jt}$ are the error terms.

**Hypothesis 1:** The aggregate *standing-on-shoulder* effects of accumulated knowledge on production are positive for both industrial varieties.

Hypothesis 1 is motivated by a straightforward policy consideration, that the output effects of industrial expansion ought to be positive over time, as long as an industry is growing and the firms are building technological capacity through manufacturing. In a cross-country estimation, we expect these two effects to be positive, or else a fundamental rethink of global industrial development philosophy would be required. However, a plausible scenario is that of statistical insignificance. Statistically insignificant estimates of the learning externalities would suggest, on average, the lack of industrial stability over time, likely caused by the frequent reallocation of production plants and offshoring activities by multinationals. The overly high frequency of product switching within industries could also cause a lack of learning effects from existing stock, thereby harming growth.

**Hypothesis 2:** The *stepping-stone* effect from imitation to innovation is positive, $(\alpha_2 + \alpha_3)/(1 - \alpha_1) > 0$. Also, $\alpha_2 > 0$ would indicate a positive contemporaneous relationship.

Hypothesis 2 is key to the understanding of development policy. The central tenet of export-oriented industrialisation policy, such as the *Flying Geese* model (Kojima 2000) popularised during the Asian Miracle era, is premised on a developing economy being able, first, to build up the industrial base by exporting goods for which it has a comparative advantage. In the early stages of development, this means imitative products. As an economy successfully builds up its knowledge base and is able to conduct indigenous innovation, as in the case of Taiwan, then the *stepping-stone* effect is positive. Nevertheless, as mentioned in the *Introduction*, many other developing economies have failed to translate export-oriented industrialisation into sustained productivity growth, with firms unable to upgrade their technological capabilities successfully. As such, estimating the magnitude of the learning effect from imitation to innovation, controlling for relevant fixed effects across countries, would go a long way towards informing industrial policy design. Is there still an economic rationale for a developing economy to first build up an industrial base on the bottom rung of the global production value chain? The result from the testing of Hypothesis 2 will inform this.

**Hypothesis 3:** The *creative-imitation* effect, that is, the knowledge spillover from innovation to imitation, is zero, $(\beta_1 + \beta_2)/\beta_3 = 0$.

After the well-documented failure of *import-substituting industrialisation* in Latin America in the 1960–70s, there is scepticism that there is a limitation to the spillover from innovation to imitation if a developing economy were to create an internal market, and allow domestic industrial leaders' innovation in driving growth for the rest of the domestic firms engaging in standardisation. Indeed, firm-level empirical studies have found conflicting results for this learning mechanism.[5] Yet some notable developing economies, especially the resource-rich ones like Malaysia, pursue a type of resource-based industrialisation policy predicated on the belief that, within the domestic market, the learning effect from innovation to imitation is large enough. To some extent, South Korea's Chaebol model fits the mould too, where the domestic knowledge spillover from innovation by the largest Chaebols is believed to generate large enough knowledge spillover to drive imitation activities by smaller players in the economy.

**Hypothesis 4:** The comparative strength of domestic industrial learning externalities is different for countries in different stages of development.

Hypothesis 4 concerns a fundamental development policy question: Should countries at different stages of development place a different focus on domestic industrial development? Intuitively, we would expect low-income economies to have significant *standing-on-shoulder* learning effects in imitation but not innovation; middle-income economies are likely to experience the strongest *stepping-stone* effect from imitation to innovation; with high-income economies expected to have the largest *standing-on-shoulder* learning effects in innovation. Knowledge of these effects would then inform policymakers of their industrial policy preferences. Lastly, the $\delta$s allow us to compare the stock and flow effects of imitation and innovation on long-run growth. Though the public capital equation is estimated as in Agénor and Neanidis (2015), the coefficients associated with public capital are not our main interest, but they allow for an empirical validation of the effects of infrastructure push in stimulating industrial expansion.

## 4. Empirical Analysis

### *4.1 Data and Measurements*

The key challenge in this study is in constructing the measures for imitative and innovative varieties. In the existing literature, innovation is measured mainly by patent applications, while imitation is measured by trademarks or employment. While patent data are a good measure for innovation, the proxies used for imitation and product variety are often flawed. Conceptually, the use of measures such as R&D employment as a proxy for product variety ceases to be valid once the scale effect is adjusted for. For another popular measure, the input measure of R&D expenditure, it is well-documented in the empirical literature to have failed in explaining innovation-driven productivity growth. The direct use of a product space-based measure is therefore essential.

The INDSTAT 4 dataset released by UNIDO provides us with sufficiently long disaggregated industrial data across countries. While INDSTAT 4 is itself an imperfect measure, it offers the most disaggregated pure domestic industrial variety data available.[6] This, coupled with the progression in product sophistication studies such as Hausmann *et al* (2007), allows us to examine empirically the interactions of imitation and innovation – as semi-symmetric ideas production functions – directly. We employ a bottom-up approach by constructing the measures using disaggregated industrial data from the UNIDO database of INDSTAT-4 2019 Revision 3, down to the 4-digit level of ISIC. While databases such as Spain's *Encuesta Sobre Estrategias Empresariales* or, more generally, trade data based on the World Customs Organisation's *Harmonised Commodity Description and Coding Systems* has more detailed product classification (potentially up to the 10-digit level), in terms of product classification, we use the UNIDO database for two reasons. Firstly, our titled aim of cross-country estimation is focused mainly on estimating the different dynamics associated with broad-based industrial transformation within an economy. Secondly, the focus is on the evolution of industrial development rather than trade policy, for which trade data will usually provide more insights. In this respect, while imperfect, the UNIDO database offers the best available data for the purposes of this study.

Another concern is the classification of industries as imitative and innovative. To minimise arbitrariness and to ensure robustness, six different pairs of imitative and innovative varieties are constructed, using a bottom-up approach. Two of these (*Innov1-Imit1* and *Innov2-Imit2*) are based on the OECD's technology intensity classification of manufacturing industries, where the first pairing considers only the high-tech ISICs as innovative varieties, while the second pairing includes both high- and medium-high tech ISICs as innovative varieties. One pair, *Innov3-Imit3*, is based on the primary industrial baskets of leading innovative economies, as defined by the country ranking of *Global Innovation Index* (INSEAD 2017).[7] Finally, three pairs are based on an income-based product sophistication index constructed, based on a similar approach to the PRODY measure of Hausmann *et al* (2007). Contrary to PRODY, our index is a production-based, weighted-average of the per capita GNIs of countries producing a given product variety, and so it represents the income level associated with said ISICs.[8]

The constructed index ranks all 4-digit ISICs along a continuum of income-based sophistication values, which then allows us to classify these ISICs using the World Bank's 2016 income-level cut-off values in grouping countries by income level. Specifically, given that the per capita GNI data used in constructing the index are based on the Atlas method, we classify the 4-digit ISICs into four groups: high-, upper-middle-, lower-middle, and low-income. After that, three innovation-imitation pairings are constructed: (i) *Innov4-Imit4*: only ISICs with high-income values are considered innovative, while only the ISICs with upper-middle-income values are considered imitation (dropping the rest); (ii) *Innov5-Imit5*: only ISICs with high-income values are considered innovative, but ISICs with both upper- and lower-middle-income values constitute imitation; and (iii) *Innov6-Imit6*: innovation includes ISICs with high- and upper-middle income values, and imitation constitutes the rest. Further descriptions of the six pairs of innovative-imitative variety measures, as well as the income-based industrial production sophistication index, are summarised in Table B1 and B2.[9]

For the benchmark analysis, the innovative and imitative varieties are proxied by the total value added of the ISIC at the 4-digit level. In other words, we measure innovation and imitation using a bottom-up aggregate measure, assuming each 4-digit ISIC to be a different type of product variety, with the respective values being the values of the variety types. For further robustness, for each of these six pairs, we repeat the same estimation exercise using two additional measures, which include the logarithm of output per employee and value added per employee. Strictly speaking, the two per-worker measures are more productivity-based measures than raw varieties. However, given the stationary nature of the variables, $m_t^R$ and $m_t^I$ in the dynamic system, the variety per-worker measures do allow for some additional robustness checks to our benchmark estimation.

On the other variables, to measure public capital we use two indicators: (i) a direct use of the recently published public capital stock data from the International Monetary Fund (IMF), and (ii) all telephone (including cellular) lines. The former is by definition the stock of public capital, while the latter is a telecommunication based public infrastructure measure that is commonly used as a proxy for advanced infrastructure (Röller and Waverman 2001; Esfahani and Ramírez 2003).[10] In line with Ang and Madsen (2013, 2015a, 2015b), we use the gross tertiary enrolment rate as a proxy for the skilled workforce. They also capture knowledge spillovers through imports, but given that our specification focuses on domestic industrial transformation we use FDI inflows instead as a controlling variable. In the growth equation, in addition to the stock effects, we also model the flows effects for both innovation and imitation. The remaining controls are standard variables employed in cross-country growth regressions, drawn from the World Bank World Development Indicators, the various statistical databases of the International Monetary Fund, and the UNESCO database for educational statistics. Further details on these variables are presented in Table B1.

Our data is in the form of an unbalanced panel, spanning 91 countries for the period 1990–2016, with a total of 1,070 observations. However, for some countries, there are missing observations. The chosen time period is largely restricted by data availability in the INDSTAT-4 database. Following the standard approach of growth regressions, we construct 3-year period averages (1990–92, 1993–95, ..., 2014–16) to minimise business cycle effects. While this leaves us with T=9, the reasonably large N means we have a maximum sample size of 495 observations. However, in actual implementation, when the use of lags as instruments and the differencing in (10) are accounted for, this drops significantly to a range of 205–332 observations. We prioritise estimating equations (7)–(10) as a system. Given the disparity of INDSTAT-4 data across countries, the system-GMM approach of Blundell and Bond (1998) is applied in favour of the difference-GMM estimator, since the latter is susceptible to the weak-instruments problem and is less efficient for data with many panels and few periods. In addition, given the importance of joint-estimation, we also apply the three-stage-least-squares (3SLS) estimator, controlling for country and time fixed effects.

*4.2 Empirical Results*

To examine the four hypotheses, we start by using total value added in the benchmark regressions, with the empirical results (for the six combinations of variety and two public capital measures) presented in Tables 1–3. For the system-GMM estimation, we treat the non-public capital control variables as exogenous. This is mainly to address the too many instruments problem (Roodman 2009), where an excessive number of instruments can result in overfitting of the instrumented variables, therefore biasing the results. While the choice of the Blundell-Bond estimator does partly mitigate the weak-instruments problem associated with difference-GMM, we restrict the lagged variable used as instruments to one period. Further, we also follow Agénor and Neanidis (2015), where the number of instruments is kept below the number of countries and subject the empirical model to various robustness tests. Since we use one-period lagged terms, the validity of the instruments can be verified indirectly by applying the Arellano and Bond (1991) test for serial correlation up to two lags. The Hansen (1982) J-test of overidentifying restrictions is also applied to check for the exogeneity of the instruments. A two-step estimator is applied, hence the use of Windmeijer robust standard errors (Windmeijer 2005). The outlined strategy with respect to system-GMM estimation allows us to reduce the risk of potential over-identification. However, the flip side is that the relatively restrictive criterion, coupled with the nature of an instrumented approach, means we have an increasing chance of a poorly-fitting model, which would result in statistically insignificant estimates. The use of 3SLS estimation is to partly mitigate this by providing a complementary approach. Lastly, the benchmark estimations of all four hypotheses are also subject to a battery of robustness tests, where the estimation is repeated using productivity measures such as output per employee and value added per employee. The estimated coefficients of the 4 industrial learning externalities are largely robust to the various specifications. These are summarised in Appendix B (Tables B3–B8).

For **Hypothesis 1**, *standing-on-shoulder* learning effects are found for both innovative and imitative varieties. Specifically, out of the 24 sets of results in the benchmark estimation, we observe statistically significant positive estimates for *standing-on-shoulder* effects in 21 of the estimated coefficients, with average elasticity values of 0.725 and 0.744 for innovative and imitative varieties respectively (0.661 and 0.714 if we included the non-significant estimates; 0.579 and 0.668 if only system-GMM estimations are considered). Although these are lower than the 0.99 estimated by Ang and Madsen (2015a), we account for endogeneity between imitation and innovation. In terms of policy implications, these estimates reaffirm the current policy consensus that within-sector learning and technological capability-building are important. To an extent, the findings also further invalidate Trump's frequent claims that trade

Table 1: Benchmark Results, where total value added are used as product variety measures

*Innov1 & Imit1, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.078 | 0.908 | 1.127 | –4.128 | –0.632 | 0.542 | 1.037 | –0.106 |
| | (0.915) | (0.573) | (0.000) | (0.585) | (0.001) | (0.002) | (0.000) | (0.874) |
| Innovation, t (log) | | 0.959 | | –3.360 | | 0.886 | | –0.405 |
| | | (0.000) | | (0.079) | | (0.000) | | (0.000) |
| Innovation, t–1 (log) | 0.539 | –0.402 | | | 0.865 | –0.767 | | |
| | (0.000) | (0.001) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.477 | | | 1.682 | 0.943 | | | –0.195 |
| | (0.014) | | | (0.403) | (0.000) | | | (0.160) |
| Imitation, t–1 (log) | –0.389 | 0.348 | | | –0.819 | 0.854 | | |
| | (0.032) | (0.001) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.304 | –0.874 | | 6.391 | 0.601 | –0.484 | | 0.721 |
| | (0.581) | (0.474) | | (0.186) | (0.002) | (0.008) | | (0.294) |
| D.Innovation [t – t–1] | | | | 3.553 | | | | 0.751 |
| | | | | (0.034) | | | | (0.003) |
| D.Imitation [t – t–1] | | | | 0.031 | | | | 1.136 |
| | | | | (0.982) | | | | (0.000) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/235 | 68/235 | 94/403 | 80/309 | 69/236 | 69/236 | 69/236 | 69/236 |
| $R^2$ | | | | | 0.963 | 0.944 | 0.943 | 0.412 |
| Number of Instruments | 37 | 37 | 46 | 42 | | | | |
| Hansen J-statistics (*p*-value) | 0.779 | 0.394 | 0.859 | 0.690 | | | | |
| AR(2) test (*p*-value) | 0.210 | 0.407 | 0.149 | 0.122 | | | | |

*Innov2 & Imit2, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.980 | 0.546 | 1.127 | –3.984 | –0.754 | 0.660 | 1.020 | 0.143 |
| | (0.666) | (0.682) | (0.000) | (0.423) | (0.003) | (0.000) | (0.000) | (0.841) |
| Innovation, t (log) | | 0.567 | | 0.995 | | 0.619 | | –0.143 |
| | | (0.001) | | (0.449) | | (0.000) | | (0.211) |
| Innovation, t–1 (log) | 0.197 | –0.302 | | | 0.789 | –0.483 | | |
| | (0.478) | (0.099) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 1.054 | | | –3.527 | 1.319 | | | –0.497 |
| | (0.000) | | | (0.005) | (0.000) | | | (0.016) |
| Imitation, t–1 (log) | –0.114 | 0.383 | | | –0.905 | 0.679 | | |
| | (0.855) | (0.036) | | | (0.000) | (0.000) | | |
| Public capital (log) | 1.021 | –0.319 | | 4.360 | 0.574 | –0.486 | | 0.411 |
| | (0.523) | (0.803) | | (0.357) | (0.027) | (0.008) | | (0.544) |
| D.Innovation [t – t–1] | | | | 1.046 | | | | 0.316 |
| | | | | (0.281) | | | | (0.126) |
| D.Imitation [t – t–1] | | | | 2.553 | | | | 1.905 |
| | | | | (0.106) | | | | (0.000) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 72/243 | 72/243 | 94/403 | 85/329 | 72/243 | 72/243 | 72/243 | 72/243 |
| $R^2$ | | | | | 0.943 | 0.953 | 0.941 | 0.419 |
| Number of Instruments | 38 | 38 | 46 | 44 | | | | |
| Hansen J-statistics (*p*-value) | 0.555 | 0.697 | 0.859 | 0.434 | | | | |
| AR(2) test (*p*-value) | 0.165 | 0.223 | 0.149 | 0.106 | | | | |

Figures in parentheses denote p-values. For System-GMM, the test statistics are calculated based on Windmeijer robust standard errors. The AR(2) test refers to the Arellano-Bond test for autocorrelation.

*Innov1 & Imit1, with public infrastructure stock (proxied by telephone measure)*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.271 | 0.040 | 1.072 | 2.629 | –2.421 | 1.952 | 0.913 | 1.782 |
| | (0.584) | (0.955) | (0.000) | (0.444) | (0.000) | (0.000) | (0.000) | (0.202) |
| Innovation, t (log) | | 0.913 | | –2.319 | | 0.959 | | –0.397 |
| | | (0.000) | | (0.157) | | (0.000) | | (0.000) |
| Innovation, t–1 (log) | 0.780 | –0.697 | | | 0.941 | –0.905 | | |
| | (0.000) | (0.002) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.684 | | | –0.370 | 0.959 | | | –0.170 |
| | (0.000) | | | (0.852) | (0.000) | | | (0.209) |
| Imitation, t–1 (log) | –0.569 | 0.614 | | | –0.785 | 0.823 | | |
| | (0.029) | (0.051) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.655 | –0.405 | | 1.954 | 2.534 | –2.010 | | –1.294 |
| | (0.042) | (0.364) | | (0.184) | (0.000) | (0.000) | | (0.380) |
| D.Innovation [t – t–1] | | | | 2.368 | | | | 0.576 |
| | | | | (0.149) | | | | (0.082) |
| D.Imitation [t – t–1] | | | | 1.908 | | | | 1.281 |
| | | | | (0.139) | | | | (0.000) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 66/220 | 66/220 | 88/369 | 73/282 | 67/221 | 67/221 | 67/221 | 67/221 |
| $R^2$ | | | | | 0.871 | 0.843 | 0.939 | 0.280 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.832 | 0.760 | 0.185 | 0.192 | | | | |
| AR(2) test (*p*-value) | 0.703 | 0.511 | 0.105 | 0.211 | | | | |

*Innov2 & Imit2, with public infrastructure stock (proxied by telephone measure)*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.365 | 0.310 | 1.072 | –2.501 | 1.803 | –1.546 | 0.920 | 2.731 |
| | (0.666) | (0.528) | (0.000) | (0.570) | (0.000) | (0.000) | (0.000) | (0.060) |
| Innovation, t (log) | | 0.577 | | –0.384 | | 0.678 | | –0.140 |
| | | (0.004) | | (0.840) | | (0.000) | | (0.228) |
| Innovation, t–1 (log) | 0.850 | –0.599 | | | 0.861 | –0.581 | | |
| | (0.011) | (0.062) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 1.066 | | | –1.858 | 1.335 | | | –0.440 |
| | (0.000) | | | (0.563) | (0.000) | | | (0.060) |
| Imitation, t–1 (log) | –0.872 | 0.589 | | | –1.090 | 0.811 | | |
| | (0.034) | (0.104) | | | (0.000) | (0.000) | | |
| Public capital (log) | –0.660 | –0.026 | | 3.940 | –2.052 | 1.767 | | –2.433 |
| | (0.182) | (0.930) | | (0.136) | (0.000) | (0.000) | | (0.106) |
| D.Innovation [t – t–1] | | | | 6.039 | | | | 0.059 |
| | | | | (0.070) | | | | (0.822) |
| D.Imitation [t – t–1] | | | | –2.472 | | | | 2.307 |
| | | | | (0.469) | | | | (0.000) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/225 | 68/225 | 88/369 | 78/295 | 68/226 | 68/226 | 68/226 | 68/226 |
| $R^2$ | | | | | 0.877 | 0.874 | 0.939 | 0.140 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.356 | 0.676 | 0.185 | 0.167 | | | | |
| AR(2) test (*p*-value) | 0.701 | 0.528 | 0.105 | 0.754 | | | | |

Estimated coefficients for non-innovation, non-imitation, and non-public capital variables are not presented to improve clarity of presentation.

Table 2: Benchmark Results, where total value added are used as product variety measures (cont.)

*Innov3 & Imit3, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.025 | 0.210 | 1.127 | –2.663 | 0.846 | –0.772 | 1.023 | 0.188 |
| | (0.981) | (0.834) | (0.000) | (0.192) | (0.000) | (0.000) | (0.000) | (0.787) |
| Innovation, t (log) | | 0.967 | | 0.164 | | 1.015 | | –0.467 |
| | | (0.000) | | (0.854) | | (0.000) | | (0.002) |
| Innovation, t–1 (log) | 0.371 | –0.237 | | | 0.833 | –0.871 | | |
| | (0.090) | (0.262) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.487 | | | 1.264 | 0.789 | | | –0.149 |
| | (0.013) | | | (0.158) | (0.000) | | | (0.296) |
| Imitation, t–1 (log) | –0.164 | 0.384 | | | –0.640 | 0.816 | | |
| | (0.375) | (0.101) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.349 | –0.540 | | 2.746 | –0.762 | 0.746 | | 0.371 |
| | (0.680) | (0.609) | | (0.663) | (0.000) | (0.001) | | (0.584) |
| D.Innovation [t – t–1] | | | | 0.186 | | | | 1.335 |
| | | | | (0.746) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 0.657 | | | | 0.784 |
| | | | | (0.150) | | | | (0.002) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 72/245 | 72/245 | 94/403 | 87/333 | 73/246 | 73/246 | 73/246 | 73/246 |
| $R^2$ | | | | | 0.952 | 0.925 | 0.942 | 0.416 |
| Number of Instruments | 38 | 38 | 46 | 44 | | | | |
| Hansen J-statistics (*p*-value) | 0.703 | 0.625 | 0.859 | 0.508 | | | | |
| AR(2) test (*p*-value) | 0.427 | 0.359 | 0.149 | 0.158 | | | | |

*Innov4 & Imit4, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.442 | –0.181 | 1.127 | 7.149 | 0.545 | –0.266 | 1.019 | 0.256 |
| | (0.645) | (0.883) | (0.000) | (0.130) | (0.016) | (0.197) | (0.000) | (0.716) |
| Innovation, t (log) | | 0.651 | | –4.102 | | 0.781 | | –0.452 |
| | | (0.000) | | (0.065) | | (0.000) | | (0.010) |
| Innovation, t–1 (log) | 0.424 | –0.309 | | | 0.731 | –0.604 | | |
| | (0.072) | (0.141) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.870 | | | 0.797 | 0.914 | | | –0.198 |
| | (0.000) | | | (0.733) | (0.000) | | | (0.198) |
| Imitation, t–1 (log) | –0.550 | 0.582 | | | –0.699 | 0.782 | | |
| | (0.071) | (0.039) | | | (0.000) | (0.000) | | |
| Public capital (log) | –0.073 | –0.019 | | –3.573 | –0.407 | 0.243 | | 0.314 |
| | (0.928) | (0.984) | | (0.262) | (0.091) | (0.264) | | (0.641) |
| D.Innovation [t – t–1] | | | | 2.890 | | | | 0.980 |
| | | | | (0.016) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 1.495 | | | | 1.147 |
| | | | | (0.000) | | | | (0.000) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 72/245 | 72/245 | 94/403 | 86/330 | 73/246 | 73/246 | 73/246 | 73/246 |
| $R^2$ | | | | | 0.946 | 0.944 | 0.942 | 0.422 |
| Number of Instruments | 38 | 38 | 46 | 44 | | | | |
| Hansen J-statistics (*p*-value) | 0.220 | 0.669 | 0.859 | 0.234 | | | | |
| AR(2) test (*p*-value) | 0.377 | 0.126 | 0.149 | 0.130 | | | | |

Figures in parentheses denote p-values. For System-GMM, the test statistics are calculated based on Windmeijer robust standard errors. The AR(2) test refers to the Arellano-Bond test for autocorrelation.

| *Innov3 & Imit3, with public infrastructure stock (proxied by telephone measure)* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SystemGMM | | | | 3SLS, with FE | | | |
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.572 | 0.083 | 1.072 | –0.903 | –1.850 | 1.555 | 0.917 | 2.149 |
| | (0.613) | (0.844) | (0.000) | (0.867) | (0.000) | (0.000) | (0.000) | (0.112) |
| Innovation, t (log) | | 0.720 | | –1.946 | | 1.130 | | –0.293 |
| | | (0.000) | | (0.579) | | (0.000) | | (0.045) |
| Innovation, t–1 (log) | 0.796 | –0.733 | | | 0.864 | –0.984 | | |
| | (0.001) | (0.024) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.649 | | | 0.053 | 0.791 | | | –0.185 |
| | (0.000) | | | (0.990) | (0.000) | | | (0.161) |
| Imitation, t–1 (log) | –0.572 | 0.978 | | | –0.670 | 0.849 | | |
| | (0.006) | (0.000) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.197 | –0.381 | | 3.280 | 2.060 | –1.718 | | –1.874 |
| | (0.467) | (0.348) | | (0.255) | (0.000) | (0.000) | | (0.204) |
| D.Innovation [t – t–1] | | | | 0.536 | | | | 2.063 |
| | | | | (0.878) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 2.945 | | | | 0.269 |
| | | | | (0.401) | | | | (0.328) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/227 | 68/227 | 88/369 | 79/298 | 69/228 | 69/228 | 69/228 | 69/228 |
| $R^2$ | | | | | 0.879 | 0.870 | 0.939 | 0.233 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.631 | 0.176 | 0.185 | 0.196 | | | | |
| AR(2) test (*p*-value) | 0.156 | 0.258 | 0.105 | 0.173 | | | | |

| *Innov4 & Imit4, with public infrastructure stock (proxied by telephone measure)* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SystemGMM | | | | 3SLS, with FE | | | |
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.366 | –0.330 | 1.072 | –1.994 | –1.679 | 1.153 | 0.920 | 1.620 |
| | (0.107) | (0.518) | (0.000) | (0.593) | (0.000) | (0.000) | (0.000) | (0.242) |
| Innovation, t (log) | | 0.687 | | –5.278 | | 0.921 | | –0.251 |
| | | (0.000) | | (0.130) | | (0.000) | | (0.151) |
| Innovation, t–1 (log) | 0.592 | –0.718 | | | 0.822 | –0.771 | | |
| | (0.002) | (0.000) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.902 | | | 3.956 | 0.947 | | | –0.250 |
| | (0.000) | | | (0.228) | (0.000) | | | (0.081) |
| Imitation, t–1 (log) | –0.844 | 1.086 | | | –0.772 | 0.823 | | |
| | (0.000) | (0.000) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.131 | 0.042 | | 4.939 | 1.883 | –1.273 | | –1.319 |
| | (0.491) | (0.904) | | (0.054) | (0.000) | (0.000) | | (0.374) |
| D.Innovation [t – t–1] | | | | 1.315 | | | | 1.645 |
| | | | | (0.704) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 1.510 | | | | 0.560 |
| | | | | (0.689) | | | | (0.056) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/227 | 68/227 | 88/369 | 78/297 | 69/228 | 69/228 | 69/228 | 69/228 |
| $R^2$ | | | | | 0.884 | 0.909 | 0.940 | 0.309 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.558 | 0.474 | 0.185 | 0.179 | | | | |
| AR(2) test (*p*-value) | 0.597 | 0.284 | 0.105 | 0.537 | | | | |

Estimated coefficients for non-innovation, non-imitation, and non-public capital variables are not presented to improve clarity of presentation.

Table 3: Benchmark Results, where total value added are used as product variety measures (cont.)

*Innov5 & Imit5, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.334 | –0.405 | 1.127 | 6.512 | 0.938 | –0.772 | 1.024 | 0.136 |
| | (0.779) | (0.723) | (0.000) | (0.021) | (0.000) | (0.000) | (0.000) | (0.848) |
| Innovation, t (log) | | 0.663 | | –3.577 | | 0.822 | | –0.465 |
| | | (0.000) | | (0.049) | | (0.000) | | (0.007) |
| Innovation, t–1 (log) | 0.325 | –0.313 | | | 0.767 | –0.655 | | |
| | (0.096) | (0.201) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.626 | | | 0.225 | 0.943 | | | –0.204 |
| | (0.004) | | | (0.905) | (0.000) | | | (0.209) |
| Imitation, t–1 (log) | –0.376 | 0.627 | | | –0.718 | 0.771 | | |
| | (0.137) | (0.035) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.149 | 0.163 | | –2.892 | –0.841 | 0.729 | | 0.453 |
| | (0.874) | (0.852) | | (0.286) | (0.001) | (0.001) | | (0.510) |
| D.Innovation [t – t–1] | | | | 2.772 | | | | 1.036 |
| | | | | (0.011) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 1.441 | | | | 1.043 |
| | | | | (0.003) | | | | (0.002) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 72/245 | 72/245 | 94/403 | 86/330 | 73/246 | 73/246 | 73/246 | 73/246 |
| $R^2$ | | | | | 0.934 | 0.930 | 0.942 | 0.411 |
| Number of Instruments | 38 | 38 | 46 | 44 | | | | |
| Hansen J-statistics (*p*-value) | 0.302 | 0.297 | 0.859 | 0.226 | | | | |
| AR(2) test (*p*-value) | 0.261 | 0.175 | 0.149 | 0.108 | | | | |

*Innov6 & Imit6, with IMF public capital stock measure*

| | SystemGMM | | | | 3SLS, with FE | | | |
|---|---|---|---|---|---|---|---|---|
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.324 | 0.368 | 1.127 | –2.448 | 1.648 | –2.055 | 1.048 | –1.293 |
| | (0.700) | (0.820) | (0.000) | (0.694) | (0.000) | (0.000) | (0.000) | (0.064) |
| Innovation, t (log) | | 0.983 | | 0.313 | | 1.077 | | –0.103 |
| | | (0.000) | | (0.887) | | (0.000) | | (0.517) |
| Innovation, t–1 (log) | 0.364 | –0.606 | | | 0.867 | –0.942 | | |
| | (0.215) | (0.117) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.807 | | | –1.657 | 0.861 | | | –0.495 |
| | (0.000) | | | (0.372) | (0.000) | | | (0.002) |
| Imitation, t–1 (log) | –0.338 | 0.556 | | | –0.620 | 0.719 | | |
| | (0.173) | (0.130) | | | (0.000) | (0.000) | | |
| Public capital (log) | –0.322 | –0.048 | | 2.452 | –1.713 | 2.141 | | 1.689 |
| | (0.663) | (0.964) | | (0.541) | (0.000) | (0.000) | | (0.016) |
| D.Innovation [t – t–1] | | | | 2.866 | | | | 2.129 |
| | | | | (0.102) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 0.454 | | | | –0.038 |
| | | | | (0.817) | | | | (0.889) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/236 | 68/236 | 94/403 | 83/316 | 69/237 | 69/237 | 69/237 | 69/237 |
| $R^2$ | | | | | 0.866 | 0.848 | 0.940 | 0.307 |
| Number of Instruments | 37 | 37 | 46 | 42 | | | | |
| Hansen J-statistics (*p*-value) | 0.434 | 0.149 | 0.859 | 0.130 | | | | |
| AR(2) test (*p*-value) | 0.885 | 0.382 | 0.149 | 0.272 | | | | |

Figures in parentheses denote p-values. For System-GMM, the test statistics are calculated based on Windmeijer robust standard errors. The AR(2) test refers to the Arellano-Bond test for autocorrelation.

| *Innov5 & Imit5, with public infrastructure stock (proxied by telephone measure)* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SystemGMM | | | | 3SLS, with FE | | | |
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | 0.133 | 0.137 | 1.072 | –2.411 | –1.611 | 1.121 | 0.920 | 2.119 |
| | (0.521) | (0.785) | (0.000) | (0.489) | (0.000) | (0.000) | (0.000) | (0.131) |
| Innovation, t (log) | | 0.720 | | –4.400 | | 0.947 | | –0.275 |
| | | (0.000) | | (0.220) | | (0.000) | | (0.112) |
| Innovation, t–1 (log) | 0.537 | –0.685 | | | 0.826 | –0.794 | | |
| | (0.021) | (0.013) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.840 | | | 3.119 | 0.938 | | | –0.242 |
| | (0.000) | | | (0.407) | (0.000) | | | (0.108) |
| Imitation, t–1 (log) | –0.656 | 0.918 | | | –0.767 | 0.824 | | |
| | (0.000) | (0.000) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.288 | –0.415 | | 4.701 | 1.801 | –1.235 | | –1.846 |
| | (0.272) | (0.279) | | (0.056) | (0.000) | (0.000) | | (0.219) |
| D.Innovation [t – t–1] | | | | 0.954 | | | | 1.758 |
| | | | | (0.803) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | 1.676 | | | | 0.441 |
| | | | | (0.698) | | | | (0.136) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 68/227 | 68/227 | 88/369 | 78/297 | 69/228 | 69/228 | 69/228 | 69/228 |
| $R^2$ | | | | | 0.893 | 0.915 | 0.940 | 0.236 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.363 | 0.390 | 0.185 | 0.148 | | | | |
| AR(2) test (*p*-value) | 0.960 | 0.348 | 0.105 | 0.356 | | | | |

| *Innov6 & Imit6, with public infrastructure stock (proxied by telephone measure)* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SystemGMM | | | | 3SLS, with FE | | | |
| | Innovation | Imitation | P.capital | Growth | Innovation | Imitation | P.capital | Growth |
| Initial GDP per capita (log) | –0.132 | –0.134 | 1.072 | –6.400 | 0.636 | –0.995 | 0.927 | 0.124 |
| | (0.755) | (0.898) | (0.000) | (0.140) | (0.000) | (0.000) | (0.000) | (0.933) |
| Innovation, t (log) | | 0.956 | | –0.607 | | 1.089 | | –0.186 |
| | | (0.000) | | (0..866) | | (0.000) | | (0.247) |
| Innovation, t–1 (log) | 0.065 | –0.356 | | | 0.853 | –0.925 | | |
| | (0.844) | (0.540) | | | (0.000) | (0.000) | | |
| Imitation, t (log) | 0.890 | | | 0.607 | 0.833 | | | –0.266 |
| | (0.000) | | | (0.767) | (0.000) | | | (0.163) |
| Imitation, t–1 (log) | –0.157 | 0.476 | | | –0.724 | 0.855 | | |
| | (0.590) | (0.055) | | | (0.000) | (0.000) | | |
| Public capital (log) | 0.168 | 0.056 | | 5.460 | –0.674 | 1.089 | | 0.234 |
| | (0.472) | (0.900) | | (0.007) | (0.000) | (0.000) | | (0.878) |
| D.Innovation [t – t–1] | | | | 5.091 | | | | 1.886 |
| | | | | (0.183) | | | | (0.000) |
| D.Imitation [t – t–1] | | | | –3.824 | | | | 0.091 |
| | | | | (0.169) | | | | (0.795) |
| Country Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries/Observations | 65/220 | 65/220 | 88/369 | 76/284 | 66/221 | 66/221 | 66/221 | 66/221 |
| $R^2$ | | | | | 0.951 | 0.939 | 0.941 | 0.418 |
| Number of Instruments | 32 | 32 | 39 | 34 | | | | |
| Hansen J-statistics (*p*-value) | 0.628 | 0.600 | 0.185 | 0.308 | | | | |
| AR(2) test (*p*-value) | 0.291 | 0.482 | 0.105 | 0.306 | | | | |

Estimated coefficients for non-innovation, non-imitation, and non-public capital variables are not presented to improve clarity of presentation.

protectionism is necessary, since organic industrial activities would lead to knowledge accumulation and subsequently, further expansion in industrial varieties. Nevertheless, a caveat is noted from the robustness testing implemented (see Appendix B), where the estimated coefficients have much lower statistical significance when the per employee numbers are used with system-GMM approach (12 out of the 24 estimated $\hat{\alpha}_1$ using system-GMM) are not significant at the ten per cent level.

More interestingly for developing-economy policies, the testing of **Hypothesis 2** reveals a statistically significant *stepping-stone* effect. All of the estimates for the contemporaneous coefficient, $\alpha_2$, are positive and statistically significant, with an average of 0.872. All but five estimates of the lagged term, $\alpha_3$, are also significant which, together with the contemporaneous term, gives an estimated average *stepping-stone* effect of 0.255. However, if we consider only the statistically significant estimates, the average drops to 0.153. In addition, for a more dynamic context to the *stepping-stone* effect, the associated multiplier effect is also calculated, which yields an average of 0.948.[11] Unlike for Hypothesis 1, the robustness testing in Appendix B reaffirms these results. This shows that the long-run impact of imitative industrial expansion on the innovative industries is positive, with a one per cent increase in imitative variety estimated to translate to just slightly below a one per cent increase in innovative variety in the long run. This provides quantitative support for export-oriented industrialisation in developing economies, which to date remains a contentious issue among policymakers.

For **Hypothesis 3**, the contemporaneous effect of the industrial learning externality from innovation to imitation is estimated at 0.845; though after accounting for the lagged terms, we have an average *creative-imitation* effect of 0.210. The dynamic multiplier associated with this *creative-imitation* effect is also calculated at 0.650 which is, surprisingly, positive. These are also robust to the additional estimates in Appendix B. The positive value indicates that innovative and imitative varieties are complements, and the expansion in innovative industries does not crowd out lower-tech industries. In the context of industrial policy design, policymakers need to recognise that industrial development should be broad-based. Any formulation of a long-term industrial development plan should place joint emphasis on both innovative and imitative industries. Given that the inherent learning effect from innovation to imitation is positive, the focus of industrial policy therefore needs to emphasise uplifting the '*capacities of smaller firms to absorb technical knowledge and processes*' (Gill and Kharas 2007). Likewise, when this result is interpreted together with the results in the growth equation (positive $\delta_5$, $\delta_6$; negative $\delta_2$, $\delta_3$), we argue that industrial policy emphasis needs to be network-based, in that the maximisation of knowledge flows are more important than stock-based policies, which corroborates the theoretical findings of Dinopoulos and Thompson (1998) and Perez-Sebastian (2007). As an example, instead of worrying about low patent-filing statistics, for developing economies industrial policies should emphasis applied research productivity, where the adoption of collaborative arrangements such as the *Triple Helix* (Etzkowitz 2008), to promote university-public sector-firm technology sharing and transfer, would unleash the many facets of expansion across all industrial varieties.

To test for **Hypothesis 4**, we repeat the same estimation exercises using annual intervals, mainly to extend the number of observations, albeit at the cost of not controlling for business cycle effects. We implement this strategy in order to estimate the model across three different samples: High-income, upper-middle-income, and low-and-lower-middle-income economies. Given the two different estimation procedures employed, for all three country-groups, we obtain 12 sets of estimates, with the averages for the key estimated coefficients of interest summarised in Table 4. For all three groups, all of the estimated *standing-on-shoulder* effects are statistically significant. However, the lower income group has much smaller estimated *standing-on-shoulder* effects compared with the other two groups, and there is no positive knowledge spillover mechanism between the two variety types.

Table 4: Annual Regressions – Estimated elasticities,
by stage of development/income grouping
(averages, using total value added as product variety measures)

| Country groups (observations) | *Standing-on-shoulder* effects | | *Stepping-stone* effect | *Creative-imitation* effect |
|---|---|---|---|---|
| | Innovation | Imitation | | |
| Low-and-lower-middle-income economies n= 67 | 0.542 | 0.513 | –0.924 | –0.464 |
| Upper-middle-income economies n=217 | 0.798 | 0.845 | 0.158 | 0.093 |
| High-income economies n=334 | 0.858 | 0.861 | 0.054 | 0.100 |

The averages are calculated based on the 12 sets of estimates for the respective groups.
Given that only regressions with annual intervals are implemented, the dynamic multipliers for the *stepping-stone* and *creative-imitation* effects are not calculated.

For the upper-middle-income economies and high-income economies, the former have a much more significant *stepping-stone* effect, while the latter register a slightly higher elasticity value of within-variety spillover from the existing knowledge stock, for both imitative and innovative varieties. In the context of development policies, this points to the need for vastly different policy prescriptions for economies at different income stages. For less-developed economies with inadequate industrial structures, the focus of industrial policy ought to be one that promotes development within-industry and, when necessary, protectionism measures may be warranted given the negative spillover effects observed across product varieties. On the other hand, for an upper-middle-income economy, growth policies need to be designed to maximise the inter-knowledge spillover among domestic industries, as the development of imitative varieties appears to be the way to indigenous innovation.

For a high-income economy, the results suggest an across-the-board industrial development strategy, given the complementary relationship between imitation and innovation. It also further invalidates *Trumpian* type claims that the era of globalisation has resulted in developing economies stealing industries from developed economies such as the United States. The strength of industrial learning externalities in high-income economies remains unrivalled compared to the developing economy groups, and industrial expansion have remained robust, not just for the innovative industries but also imitative industries based largely on standardised manufacturing.

## 5. Conclusion

The main purpose of this study is to estimate the four different domestic industrial learning externalities of and between imitation and innovation. Using highly disaggregated industrial data as measures for product varieties, and having developed a theoretical framework to provide the necessary analytical basis, we test for the relationship between imitation and innovation based on four policy-relevant hypotheses. In sum, we document a robust and statistically significant *stepping-stone* effect of imitation on innovation, and a reverse positive *creative-imitation* effect from innovation to imitation, albeit at a slightly lower magnitude than the *stepping-stone* effect. Likewise, we also estimate positive within-sector learning effects for both innovation and imitation, albeit at lower statistical significance. Fostering sustainable productivity growth and innovation goes beyond the fixation on R&D funding and patent filing, which in turn requires making the right trade-offs in creating an overall industrial system that enables industrial learning externalities to flourish. These empirical findings therefore have important implications for industrial policies designed to foster innovation-driven growth, especially in middle-income and developing economies.

First, the direct learning effects within both imitation and innovation are largely positive. Although the limited statistical significance suggests that industrial sustainability in certain groups of developing economies may be in doubt, raising questions about the overall effects of multinationals' offshoring and plant relocation activities on developing economies' long-term economic prospects, the fact that the high-income economies register significant positive effects indicates that the growing political rhetoric observed in some developed economies (developing economies stealing industries from developed economies) are flawed and inaccurate. Second, both the positive *stepping-stone* and *creative-imitation* effects suggest that innovation and imitation ought to be complementary. The success stories of Taiwan and South Korea likely reflect their respective ability to maximise the benefits associated with these two sources of industrial learning externalities. There are, therefore, inherent merits in policies such as export-oriented industrialisation and resource-based industrialisation, provided that measures are put in place to support and uplift the capacities of smaller firms to absorb technical knowledge and processes. Third, we also argue that industrial policy emphasis needs to be network-based, in that the maximisation of knowledge flows is more important than stock-based policies. This would better facilitate a broad-based domestic industrial expansion than overly narrowed and targeted policy focus.

Finally, for future research extensions, given that the empirical implementation in this paper is largely conditioned by data availability, there are obvious improvements that can be implemented. In terms of the theoretical specification, the model setup here neither explicitly accounts for the different types of foreign investments, nor the effects of inter-industry trade within an economy. Prior to this study, most of these elements are modelled in the niche area of computational general equilibrium (CGE) studies. The rich information on highly disaggregated industrial production – hence the different product varieties – are often contained in input-output tables and specialised manufacturing surveys. The use of these would allow for a more elaborate empirical examinations based on rigorous theoretical growth models of variety expansion-based growth, such as one that includes intra- and inter-industry trade, at cross-country level.

*Accepted for publication:* 19 March 2020

## Endnotes

1. King Yoong Lim: Corresponding author, Nottingham Business School, Nottingham Trent University (Email: king.lim@ntu.ac.uk); Ali Raza: Leeds University Business School. Helpful feedback and suggestions from Gerald Steele, Kwok Tong Soo, and 4 anonymous referees are gratefully acknowledged. King Yoong Lim would also acknowledge the research grant, AP-2017-003/1: ASEAN Connectivity: A Multifaceted Approach from the Ministry of Higher Education Malaysia for his involvement in this article. The views expressed are our own. Appendices A and B can be made available upon request.

2. For big-picture views of the structural issues plaguing upper middle-income economies, see the literature on middle-income traps (Gill and Kharas 2007; Eichengreen *et al*, 2014; Agénor 2017).

3. See East Asia-based studies such as Nelson and Pack (1999), Amsden (2001) and Zeufack and Lim (2013).

4. Our studies are closest to the two empirical papers of Ang and Madsen (2015a, 2015b). However, in the former they do not account for the interaction between innovation and imitation, while in the latter an asymmetric specification is used for the two sectors. Also, in both studies, the endogeneity between the two sectors is not properly accounted for.

5. See empirical studies in the area of international production networks, such as Athukorala and Hill (2010), for positive evidence, and studies such as Djankov and Hoekman (2000) for negative effects.

6. Technically, trade data have a much more detailed classification. An example is the *Harmonised Commodity Description and Coding Systems* developed and maintained by the World Customs Organisation, which potentially has product classification to the 10-digit level. Nevertheless, the main focus of this paper is in examining the industrial dynamics within a country undergoing transformation. As such, we use a pure industrial variety dataset.

7. This imitation-innovation pairing, *Innov3-Imit3*, is constructed by first identifying the top five ISICs (in terms of output value) respectively for the five most innovative economies in the world, as defined by the average rankings of the countries over 2013–17. These five economies are Singapore, Switzerland, Ireland, Slovakia, and Germany. These ISICs identified (down to the 4-digit level) constitute innovative varieties, while the rest constitute imitative varieties.

8. Specifically, for the index, the product sophistication level associated with an ISIC $k$ is given by $\sum_j \frac{z_{jk}/Z_j}{\sum_j (z_{jk}/Z_j)} Y_j$, where $z_{jk}/Z_j$ is the share of value-added of the product variety in country *j*'s overall production basket. The denominator aggregates these value shares across all economies. As such, the weights correspond to the revealed comparative production strength of a country in variety $k$.

9. By design, the use of the six pairs of innovative-imitative variety measures is for robustness purposes. By construction, the OECD-based *Innov1-Imit1* measure, the income content-based *Innov4-Imit4* and *Innov5-Imit5* measures have a relatively strict interpretation as to what product variety constitutes innovation. On the other hand, the other OECD-based measure, *Innov2-Imit2*, and the income content-based pair of *Innov6-Imit6* have a broader definition of innovation, where products in the medium-high-tech industries (or industries with the sophistication content of upper-middle-income economies) are also classified as innovative varieties. Lastly, the *Innov3-Imit3* pair classify industries based solely on their significance in the overall industrial production of the top five most innovative economies in the world. Overall, these different measures therefore implicitly allow for robustness checks of the estimated elasticities, regardless of how strictly innovation ought to be interpreted.

10. There are also other indicators of public infrastructure that can be used as alternative measures, as discussed in Romp and de Haan (2007) and Straub (2008). However, the main coefficients of interest in this paper are not associated with the public capital measure. Moreover, existing empirical studies show that the different measures tend to give similar elasticities. Extra robustness analysis for infrastructure is therefore not explored.

11. The value quoted is the average of the 12 values. Given the three-year averaging, this estimate is therefore valid in the context of a six-year period, covering the usual five-year horizon of most medium-term development plans in developing countries. Also, given that the estimated results are mostly free from second-order autocorrelation, the long-term elasticity should be close to the estimated figure.

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