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Technology-Intensive Exports, R&D, Human Capital, and Economic Growth in the Twenty-First Century

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TECHNOLOGY-INTENSIVE EXPORTS, R&D, HUMAN CAPITAL, AND ECONOMIC GROWTH IN THE TWENTY-FIRST CENTURY

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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CONTENTS

ABBREVIATIONS

AAZ: Referring to Acemoglu, Aghion, and Zilibotti (Acemoglu et al., 2006)

ABOV: Moment conditions proposed by Arellano & Bover (1995)

AS: Moment conditions proposed by Ahn & Schmidt (1995)

AI: Artificial Intelligence

BGP: Balanced Growth Path

CCE: Constant Correlated Effects assumption in GMM estimation

GDP: Gross Domestic Product

GERD: General Expenditure on Research and Development

GMM: Generalized Method of Moments

H-O: Referring to Heckscher-Ohlin trade theory and model

HNR: Moment conditions proposed by Holtz-Eakin et al. (1988)

ICT: Information and Communications Technologies

OLS: Ordinary Least Squares estimation method

PPP: Purchasing Power Parity

PWT: Penn World Table

R&D; Research and Development, often referring to research and development expenditure

STD: GMM Standard Model Assumptions

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ABSTRACT

TECHNOLOGY-INTENSIVE EXPORTS, R&D, HUMAN CAPITAL, AND ECONOMIC GROWTH IN THE TWENTY-FIRST CENTURY

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This thesis investigates twenty-first century economic growth through a distance-to-frontier (technology-gap) lens where growth in a country's knowledge stock is determined by knowledge creation and knowledge imitation. The creation term is assumed to be a function of research and development, technology-intensive export performance, and human capital, while the imitation term is a function of the technology gap, technology-intensive export performance, and human capital. Over the period 1997-2018, two samples of countries are analyzed in a panel setting, and two growth models are estimated in total—one for each sample.

While research and development has been extensively analyzed in the economic growth context, many studies are limited to small samples of countries. In this paper, the growth model pertaining the large sample of countries ($n = 57$) utilizes total R&D expenditure data. The smaller sample ($n = 41$) considers a growth model wherein government-funded and business-enterprise-funded R&D expenditure are considered as separate knowledge determinants.

Until recently, technology-intensive export data were sparse, making variable construction difficult for large-sample analysis. While a traditional approach might utilize information and communications technology measures in the growth model, I take advantage of modern data availability and introduce a measure of technology-intensive export performance to the conceptual and empirical models.

To investigate the factors shaping knowledge over time, unconditional β-convergence tests are conducted on the proposed determinants of knowledge.

The results of these tests indicate convergence in technology-intensive export performance, human capital, and government-funded research and development expenditure across nations—suggesting that less-developed nations are "catching up" to the leaders in terms of knowledge (technology). The growth models are estimated utilizing various generalized method of moments estimators. Of the three research and development variables, results indicate that only government-funded research and development expenditure has a positive effect on growth. Technology-intensive export performance, and human capital are shown to have positive and significant growth effects for all models and samples considered. Overall, these results suggest that policymakers should give great consideration to technology-intensive export performance and human capital when drafting growth policies.

1 Introduction

1.1 Background

What makes an economy grow? More specifically, what factors determine economic growth? The first investigators of these questions theorized that cross-country differences in the supply of capital and labor would be the key contributors to growth rate differences. Although an intuitive hypothesis, empirical results revealed that capital and labor supplies play a smaller role in economic growth than a third factor determining the effectiveness of labor: technological progress (Abramovitz, 1956; Solow, 1956, 1957). This is the basis upon which modern economic growth theory is built.

The purpose of this research is to investigate the determining factors of knowledge and how these factors might explain the economic growth-rate landscape from 1997 to 2018 for selected countries. So, in the proceeding sections I build upon the economic growth literature by proposing and analyzing a unique set of knowledge-stock determinants in a panel-model setting. As is the case with all economic modeling efforts, economic growth models—including the models in this paper—are simplifications of a complex international economic system.

The contribution offered in this research is derived from a conceptual approach that leads to a unique set of independent variables in the growth model. Although research and development (*R&D*) has been studied extensively in the economic growth context, I investigate R&D in two different ways: total R&D (conventional approach) and R&D decomposed by source of funds (the two sources being government and business enterprise). The other unique variable is a measure of technology-intensive export performance. Considering technology-intensive export performance and the role of R&D may produce insights of interest to policymakers and inspire future discussions.

Some terminology must be discussed before proceeding. In the context of economic growth, the terms *gross domestic product* (*GDP*), *output*, *economic output*, and *income* are considered synonymous in this thesis. Economic growth is traditionally analyzed based on a GDP per capita basis, so for example, the terms *per capita output* or *income per person* refer to GDP per capita.

The discussion surrounding quantity versus quality of growth is worth mentioning (Kuznets, 1962). Simply dividing a country's GDP (market activity) by its population ignores the underlying income distribution and therefore may not accurately reflect the true living standards experienced within its borders. While acknowledging that GDP per capita is, in many cases, a poor societal thermometer, I proceed with this research with the understanding that I am conducting an analysis of economic growth *quantity*. Constructing improved metrics measuring societal well-being is certainly a worthwhile endeavor, and while work on this front is gaining momentum (e.g., Stiglitz et al., 2019), the scope of this analysis is restricted to investigating the factors determining economic growth.

1.2 Research Objectives

Given the vastness of economic growth as a research topic, it is essential to limit the scope of this thesis to some degree. The aspects of economic growth analyzed in this thesis can be synthesized into three research objectives, each of which is analyzed in a panel-data setting with annual data spanning from 1997 to 2018. These objectives are structured to guide this research in a quest to understanding cross-country economic growth rate differences in the twenty-first century. The objectives are to:

1. Describe the modern dynamics of the proposed knowledge-stock determinants through a modified β-convergence lens.
2. Investigate the relationships (and significance) of the following variables with respect to GDP per capita growth:

- Technology-intensive export performance
- R&D
- Human capital
- Technology gap

3. Utilizing the methods employed in objectives one and two, identify how government-funded and business-enterprise-funded R&D differ in their relationship to GDP per capita growth.

Completion of these objectives will offer a contribution to the literature, a prompt for further research, and useful insights for policymakers and economists alike.

1.3 Motivation

International nation-level research and development expenditure data have been sparse in the past, so many technology-gap models have resorted to other metrics in attempts to capture innovative activity in large-sample settings. For example, patenting activities (Fagerberg, 1987), scientific journal article publication statistics, or a combination of the two (Castellacci, 2011) have been used to this effect. Although still not perfect, data are now available for a relatively large (n=57) set of countries—spanning a sufficient time frame for the approach used in this thesis. Additionally, for a smaller (n=41) set of countries, data containing R&D expenditure by source of funds are available. The current accessibility of these data allows the direct use of R&D expenditure as an indicator of innovative activity in place of patenting and publishing statistics.

Technology-gap models assume that knowledge growth depends upon knowledge creation and knowledge imitation, and a country's potential for imitation is determined by its relative distance from the leader (difference in GDP per capita). How effectively a country exploits this gap (*absorptive capacity*) is a key aspect of technology-gap growth models. In addition depending upon human capital, absorptive capacity is often assumed to depend upon technological infrastructure. Information and communications technology (ICT) measures have commonly been used as indicators of technological infrastructure in the literature (Castellacci, 2011). Instead of ICT, I propose and construct a unique, alternative indicator to capture how effectively countries exploit technology gaps: technology-intensive export performance. To my knowledge, analyzing cross-country economic growth rates utilizing technology-intensive export performance and R&D expenditure data has not been previously attempted. This research is motivated by the potential insights to be gained stemming from the approach taken.

2 Literature Review

2.1 Economic Growth Theory

In 1956, Robert Solow laid the foundations of neoclassical growth theory by developing an exogenous growth model (Solow, 1956).[1] In the Solow growth model, economic output (Y) is a function of capital (K), labor (L), and knowledge (A) where A and L are related multiplicatively. This relationship allows for interpreting A as the effectiveness of labor, so any growth in A is labor augmenting. Economic growth in the Solow model is explained by capital accumulation, population growth, and technological progress (growth in the knowledge stock), where the rates of population growth and technological progress are exogenous parameters.

An issue with the Solow model is that A does not have an explicit definition. Conceptually, A might be technology or knowledge, but in reality, A is a compilation of all factors affecting output which are not capital or labor. Growth accounting

[1]Swan (1956) also developed this model independent of Solow in a Newton-Leibniz type simultaneity. I refer to this exogenous growth model as the "Solow growth model," so to avoid potential confusion, only Solow is mentioned in the narrative.

(Abramovitz, 1956; Solow, 1957) provides a template for quantifying the role each factor of production plays in the output growth process. In a growth-accounting empirical analysis, Solow (1957) determined that from 1909 to 1949, 87.5 percent of US labor productivity gains were attributable to technological progress, and only the remaining 12.5 percent were due to increased capital intensity. Solow's theory, model, and empirical results inspired a wave of economic growth research with variations such as including human capital in the Solow framework (Mankiw et al., 1992), developing endogenous growth models (Aghion & Howitt, 1990; Romer, 1986, 1990), and developing distance-to-frontier growth models (Acemoglu et al., 2006; Vandenbussche et al., 2006).

A prediction of the Solow model is that countries will converge in output growth rates over time. In other words, it expects countries with lower levels of per capita income to grow faster than those with higher income levels. The Solow growth model implies that all countries converge to their balanced growth path (BGP) and that capital exhibits decreasing returns. Since countries below their BGP have higher returns to capital relative to a country already on the BGP, we expect capital to flow from high to low-income countries, and therefore lower-income countries can be expected to grow at a higher rate.

Although a comprehensible story, empirical β-convergence analyses reveal mixed results.[2] Drawing from various sources, Aghion & Howitt (2005) provide a review of studies that analyze convergence empirics, and conclude that convergence is far from universal. In fact, from the late nineteenth century to the mid twentieth century, the world experienced significant divergence—the gap between rich and poor countries widened greatly during this period. But in the latter half of the twentieth century, patterns of convergence emerged in the form of *club convergence*; that is, the rich and middle-income countries converged toward one common long-run growth rate,

[2] The "β" in β-convergence stems from the linear-regression-model framework used to analyze convergence. The coefficient of interest in these models is denoted β.

and the poorest countries exhibited growth-rate diversity. Although convergence was experienced within the higher-income group, the convergence pattern between the rich-to-middle income and poorest clubs remained one of divergence during this period.

If we want to understand cross-country income differences, we could define A as a set of determinants and investigate the role each element plays in the growth process. Since β-convergence analysis on per capita income helps us understand *if* growth rates differ, could we use the same methodology on the knowledge-stock determinants to understand *why*? Utilizing a growth accounting framework, Castellacci (2011) conducted convergence tests on the determinants of A. This simple empirical procedure's results may provide helpful insights and it is integrated into my analysis.

2.2 Technology Gap (Distance to Frontier)

In 1961, Michael Posner (1961) developed a conceptual model of cross-country innovation dynamics in the Heckscher-Ohlin (*H-O*) framework. The theoretical model presented analyzes the trade of innovative, technological products between two counties and the *lags* between the two countries. To illustrate: consider a single industry in two countries, P and Q, beginning in a state of no-trade equilibrium where P is an innovating country with relatively high wages and Q seeks to imitate innovations with relatively low wages. Suppose P develops a new technological product after some innovative gestation period. P will export this new product to Q after some finite demand lag. This demand lag concludes when, after being introduced to the new product, Q wishes to diffuse, and therefore import this product from P. Following the expiry of a finite imitation lag (where Q learns how to produce the product domestically), Q will produce this technological product with lower wages and restore its current account to balance by exporting the imitated product back to P. These lags, Posner argued, are largely determined by Q's social infrastructure (e.g., communication networks, trade and openness policy, culture). This model implies that knowledge evolution is determined by innovation (by country P) and imitation (by country Q)—concepts of both technology-gap and distance-to-frontier economic growth models developed after Posner (1961).

Fagerberg (1987) empirically investigated cross-country growth rate differences with a technology-gap approach. Fagerberg argued that, at the time, no other empirical analysis had produced results which could be interpreted as proving or disproving the hypotheses of technology gap theory. In contrast to the statistical methodology utilized in the past, Fagerberg used a pooled time-series cross-country data set and constructed two versions of economic growth models. The first, so-called *supply-side* model expresses output as a function of its lagged level, patenting activity, and investment where, Fagerberg argued, the three explanatory variables respectively correspond to potential for imitation, innovative activity, and institutional strength (likely influencing potential for imitation). A second, so-called *Keynesian* model uses the same explanatory variables expressed as an index relative to the average in the sample (average = 1). This model also includes a variable of growth in world exports which is not expressed relative to average.

Fagerberg (1987) calculated Spearman rank correlations between GDP and technological level variables for various subsets of years from the 1960's to 1980's. The results showed a statistically strong and positive relation between economic and technological levels (as measured by either patent statistics or civil R&D investment), supporting the general hypothesis of the technology gap theory. OLS regression results of the technology-gap model of economic growth displayed high explanatory power overall. The Keynesian model (containing variables compared to averages) yielded higher explanatory power than the supply-side model for each of the samples tested. The models fit less well when using samples of small and medium-sized countries, providing potential support for the idea of club convergence (as mentioned in Aghion & Howitt, 2005).

Fagerberg (1987) discussed the difficulties surrounding data availability, especially for obtaining R&D statistics for less-developed economies. It is unclear whether R&D expenditure was the ideal variable, but since data availability prohibited its use, patenting statistics were used instead. One could construct the argument that patenting statistics better capture cross-country institutional differences in the innovation sector, but I believe many technology-gap growth models opt for patent statistics because R&D expenditure data have been largely unavailable. Since R&D data are now available for a relatively large set of countries, I use R&D expenditure statistics directly; the use of R&D data provides new and unique insights.

Acemoglu et al. (2006) (AAZ) investigated "relative backwardness" by developing a distance-to-frontier growth model with an emphasis on the roles of human capital and R&D in technological progress. This "backwardness" concept comes from Gerschenkron's (1962) essay in which he argued that "backward" countries (those further from the technological frontier) stand to gain—with sufficient investment—by adopting technologies from the frontier. In the AAZ model, entrepreneurs engage in both innovation and adoption which implies relatively "backward" economies can derive technological progress by adopting (imitating) technologies from the frontier. Countries further from the frontier partake in an investment-based strategy that emphasizes adopting well-established frontier technologies, and those closer to the frontier place emphasis on innovation, i.e., producing new technologies.

For the purposes of my research, the distance-to-frontier modeling approach is nearly indistinguishable from technology-gap approaches such as those used by Fagerberg (1987). Both approaches suggest that a country's knowledge evolution is determined by a combination of imitation and innovation and that countries further from the frontier (those having a larger technology gap) engage more in imitation than innovation. Although I employ a different configuration, this core concept is what my model is built to capture.

Castellacci (2011) approached cross-country income growth by developing a model where innovation and imitation are decomposed into a set of determinants. This approach allowed Castellacci to dissect and understand the factors determining the evolution of knowledge. Patenting and scientific journal article publication statistics are included in the growth model as measures of innovative activity, and they are considered as separate entities. Similar decomposition procedures are followed for the technological infrastructure (various ICT metrics) and human capital (primary and secondary education, literacy rates, etc.) variables. My approach to model development loosely follows Castellacci (2011) because it permits separate consideration of government and business-enterprise funded R&D expenditure.

The *concepts* behind technology-gap models and distance-to-frontier models are, broadly speaking, nearly identical. A distance-to-frontier model (e.g., AAZ) might use Gerschenkron's (1962) idea of "backwardness" as a proxy for imitation opportunities, but another growth model of might use an identical proxy, get named a technology-gap model, and cite Posner (1961). It appears that expressing a preference for one term over the other is derived from researchers' specialization. On one hand, those specializing in international economics and trade and interested in growth would be familiar with the H-O framework and Posner's technology-gap extension, and might also think of international technology dynamics in terms of Vernon's (1979) product cycle model. In that case, utilizing the "technology-gap" terminology would be the logical choice. On the other hand, those specializing in growth and development might construct a growth model with Gerschenkron (1962) in mind, whose idea of "backward economies" fits neatly into the growth-model framework. In the latter case, constructing a *distance* variable and including it in the growth model's set of explanatory variables would appropriately follow the "distance-to-frontier" terminology. With identical sets of covariates and the model specifications, these two models would be the same, although their terminologies would be different. While model and terminology choice may be more nuanced in practice than in this example, for the purposes of my research, the two terms are interchangeable.

2.3 Technology-Intensive Exports

The economic growth model developed in the following sections utilizes relative technology-intensive export performance as an indicator of a country's absorptive capacity. This idea was motivated, in large part, by Lall's (2000) analysis of technological export structures in developing countries. Lall offers an export classification system in which products are considered resource-based, low-technology, medium technology, or high-technology based on the amount of technological activity involved in the manufacturing process. According to this scheme, resource-based products are labor-intensive and generally simple to manufacture; high-technology products require high levels of R&D investment, highly specialized labor, and sophisticated technology infrastructures. What role do these high-technology exports have in the growth and development process? According to Lall, high-technology products have potential for learning, knowledge spillovers, and attracting foreign investment.

From 1985 to 1998, developing countries outpaced developed countries in high-technology export growth by 10.1 percentage points (Lall, 2000). This result is counterintuitive to conventional trade theory which suggests developed countries should outperform their developing counterparts in technology-intensive export performance. Lall's (2000) results suggest a pattern convergence in technology-intensive export performance. In the β-convergence section of this paper (Section 4.3), I examine if this phenomenon was present from 1997 to 2018.

Daniels (1999) empirically investigated if technology-intensive trade success has a positive effect on economic performance. At the time, few empirical studies had been conducted on the topic.[3] According to Daniels, policymakers assume that technology-

[3] Daniels (1999) analyzed other trade-related metrics in addition to exports, so when referring to

intensive trade performance has a positive effect on economic performance. Daniels' (1999) primary objective was to summarize a detailed statistical analysis between technology-intensive trade and economic growth. Daniels tested the hypothesis that technology-intensive trade performance has a positive effect on GDP per capita (as a proxy for economic performance and prosperity) using data from approximately 45 countries from 1978 to 1992. The empirical investigation was based on cross-country observations of technology-intensive trade performance and GDP per capita, a one to two-year lag between the independent (trade and physical capital) variables, and the dependent (change in GDP per capita) variables over time. Rather than using the conventional measure of percentage change in GDP per capita (which is contingent upon base-year income levels), Daniels utilized absolute change in GDP per capita levels as the focal point in his study. Although all period average trade variables were found to be statistically significant and positively associated with the absolute income measure, the associations were only mildly or moderately positive.

Growth and trade models such as endogenous growth theories are primarily concerned with endogenizing growth and technology; Daniels argued that this approach is at odds with the neoclassical conclusion that the contributors to growth are often exogenous. Because Daniels sought to measure the effects of technology-intensive trade on growth, he utilized the extended technology-gap model by Dosi et al. (1990) rather than an endogenous growth model. Although Dosi et al. (1990) sought to assess sectoral technology spillover effects, the mechanism of action (pervasive spillover effects of technology investment on productivity and growth) might also apply at the macroeconomic level. Empirical studies analyzing technological change as an economic process (Daniels, 1996; e.g., Fagerberg, 1988; Lichtenberg, 1992) have largely reaffirmed that nations with high technology-intensive trade performance have superior economic performance. None of these previous empirical analyses utilized the comprehensive

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Daniels, I must use the language: technology-intensive *trade* as opposed to *exports*.

approach taken by Dosi et al. (1990) which features a positive feedback loop from investment in technology through productivity.

Daniels used revealed comparative advantage and international trade competitiveness indicator metrics in addition to physical capital investment in his multiple regression model. This narrow focus on growth influences is both intentional and acknowledged in the paper. Since there are a large number of potential growth influences to choose from for a regression, Daniels included a capital investment variable—based on conclusions by Levine & Renelt (1992) that capital investment has the most consistent and robust correlation with growth across nations. Daniels concluded that the policy assumption—that technology-intensive trade performance is positively associated with economic performance—should not be unconditionally followed by all nations because, although positive, the relationship between technology-intensive trade and economic performance was small and inconsistent. Although differing in methodology, my research reinvestigates the results and associated conclusions of Daniels (1999).

3 Conceptual Model

Before proceeding, I would like to draw attention to a passage from Durlauf et al. (2005) which motivates the development of my conceptual model:

> "One dominant theme will be that the empirical study of growth requires an eclectic approach, and that the field has been harmed by a tendency for research areas to evolve independently, without enough interaction.[4] This is not simply a question of using a variety of techniques: it also means that there needs to be a closer connection between theory and evidence, a

[4]Quoting the footnote from Durlauf et al. (2005): "To give a specific example, the macroeconomic literature on international technology differences only rarely acknowledges relevant work by trade economists, including estimates of the Heckscher-Ohlin-Vanek model that suggest an important role for technology differences. See Klenow and Rodriguez-Clare -Klenow & Rodriguez-Clare (1997) for more discussion." p.128.

> willingness to draw on ideas from areas such as trade theory, and more attention to particular features of the countries under study."
>
> Durlauf, Johnson & Temple (2005), pp. 128-129.

The conceptual model presented in this section draws upon trade theory to create a growth model which respects the relationship between technology-intensive export performance and growth (Lall, 2000). One can observe the importance of integrating across economic fields by surveying the macroeconomic models studied by university students (many of which stem from microeconomic foundations). In my view, it therefore makes sense to develop a growth model which recognizes and incorporates the relevant empirical findings from trade economists.

The importance of knowledge in the economic growth process is well known and extensively analyzed. An issue growth economists face is defining which variables (of which there are endless possibilities) determine knowledge (A) and its evolution; economists may select knowledge or (more generally) income growth determinants based on some combination of relevant theory, past empirics, and their research objectives. Conclusions and insights regarding the selected determinants are most often drawn from the model estimation (summary statistics and coefficient estimates).

I considered two approaches for developing a model to be estimated in this paper. First, Durlauf et al. (2005) offer a general growth model template that allows for easily plugging in a set of explanatory variables and proceeding to estimation. The cross-country growth regression is represented as: $growth = \beta \log y_{i,0} + \Psi S_i + \Upsilon Z_i + \varepsilon_i$, where $\log y_{i,0}$ and the set S_i combine to represent the growth determinants suggested by the Solow model, and Z_i represents the set of alternative growth determinants of interest.[5] This representation provides clear accessibility and extendability; when investigating many sets of alternative growth determinants, the "plug-in" nature may be appealing. As pointed out in Durlauf et al. (2005), these models are sometimes

[5]The original model from Durlauf et al. (2005) is $\gamma_i = \beta \log y_{i,0} + \Psi X_i + \pi Z_i + \varepsilon_i$. To avoid future confusion, I have altered some variable names.

referred to as "Barro models" because of Barro's extensive research into alternative growth determinants (Barro et al., 1991).

The alternative approach I considered is to begin with a production function (e.g., a generic Cobb-Douglas or CES) and then derive a growth model for estimation such that the relationships between explanatory variables are defined. I opt for this latter approach to model development because I want to make clear the transition from theoretical arguments to the empirical model. In the context of this paper (and technology gap theories of economic growth in general), relationships among determinants are imperative. So in developing my conceptual and empirical models—for the purposes of clarity and transparency—I begin with a basic aggregate production function, and I document the theoretical underpinnings in each step of the process of developing the final growth models. To be clear, the two methods can produce identical empirical models, but in the technology-gap context with only two sets of alternative determinants, generating a conceptual model in the Barro-model framework could lead to unfortunate simplifications of the underlying theory.[6]

My model specification argues that for a single country, per capita GDP growth depends upon knowledge stock growth and capital investment. In the literature, the alternative terms *technical progress* and *productive capital accumulation* are sometimes used instead of knowledge stock growth and capital investment, respectively (Bénassy-Quéré et al., 2010; Maddison, 1997).[7] For now, investment is set aside and considered a proximate determinant (i.e., an element of S_i in a Barro-like framework). Technology-gap theory suggests that knowledge evolves according to two processes: knowledge creation and knowledge imitation. Knowledge creation is produced in the research and development sector; therefore innovative efforts and R&D sector productivity determine the amount of knowledge created over some time interval. The knowledge

[6]One could derive an identical conceptual model from the Barro-model framework as well, but I prefer beginning with an aggregate production function in the context of this paper.

[7]Both sets of terms often correspond to gross fixed capital formation.

imitated (absorbed) by a country is determined by its technology gap (distance to frontier) and how effectively the country exploits this gap. This "effectiveness of gap exploitation" is often referred to as *absorptive capacity*, although Lall (2000) offers an alternative term, *absorptive capability*. Since the *absorptive capacity* language appears more frequently in the technology-gap literature, I refer to the aforementioned exploitation-effectiveness as *absorptive capacity*.

So far, the conceptual model suggests that per capita income growth is determined by investment, innovative efforts and R&D sector productivity, and a technology gap and absorptive capacity. Innovative efforts could be represented by numerous indicators, but contrary to some technology-gap growth models (Castellacci, 2011; e.g., Fagerberg, 1987) I forgo the commonly-used patent statistics and opt for general expenditure on research and development (R&D expenditure). Beyond total R&D expenditure, I propose a second, nearly identical model for investigation, where R&D expenditure funds are considered separately by their source (business enterprise, government). R&D sector productivity is critical because expenditure alone does not promise knowledge creation. Of the many potential R&D-productivity determinants that could be introduced at this point, technology-gap theory and empirics suggest two: technological infrastructure and human capital. Likewise, absorptive capacity is also comprised of technological infrastructure and human capital. R&D expenditure cannot create new knowledge, innovate, or lead to GDP growth alone: a country with high absorptive capacity must have sufficiently educated and skilled workers in addition to complementary technological infrastructure which supports these workers. The combination of the two is imperative—for example, consider a chemist without a laboratory, or a laboratory without a chemist. Similarly, a technology gap (the potential for imitation) can only be exploited if a sufficient complement of technological infrastructure and human capital exists (see Figure 1 for a visual representation of the conceptual model).

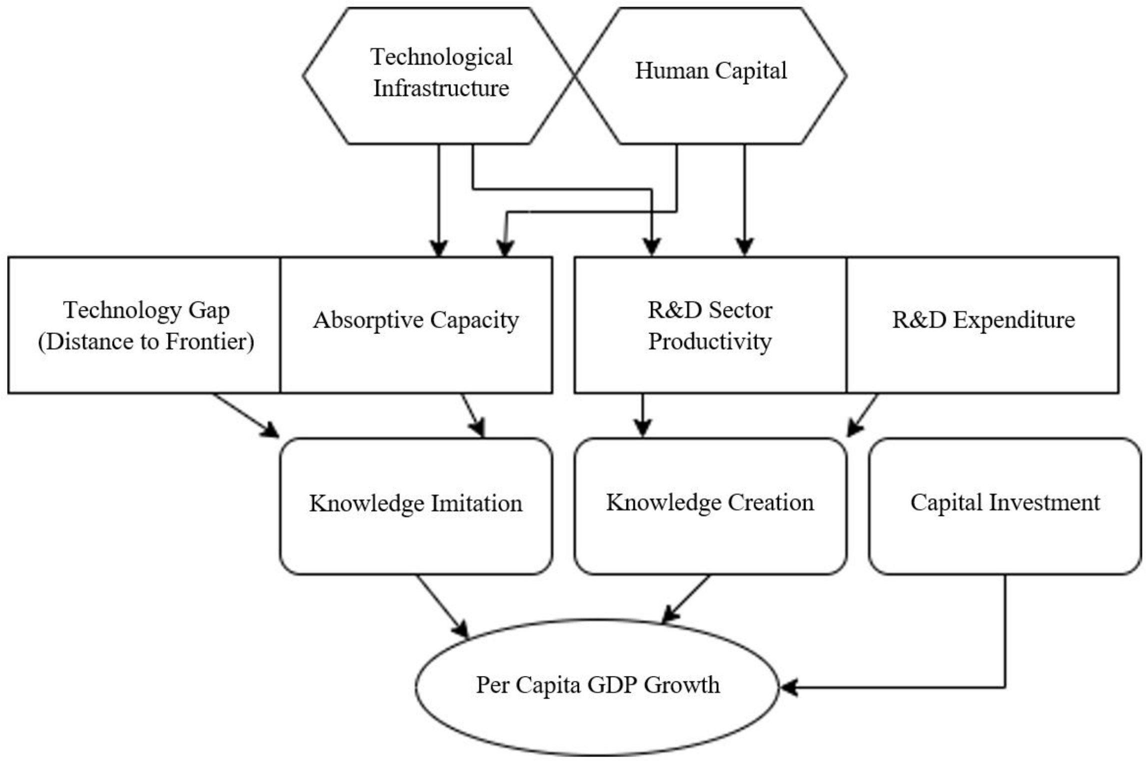

Figure 1: Model Visualization

Technology-intensive export performance enters the model as the technological infrastructure variable. Various ICT measures are commonly used as indicators of technological infrastructure, but technology-intensive export performance provides an advantage in that it complies with the suggestion in Durlauf et al. (2005). The definition of an ICT index must change over time which could make the index, in a sense, inconsistent over a large time interval. Consider the case of conventional ICT measures such as internet accessibility and cellular network coverage: these technologies were likely crucial to economic growth and development in the beginning years of my sample (late 1990's), but technologies and computational abilities expanded massively by the end of the sample (late 2010's). For example, artificial intelligence (AI) is now a focus of "ICT and growth" research (and for good reason, see Aghion et al., 2019 for a thought-provoking model and discussion), but I question whether any ICT index would have included an AI element in 1997. My argument is not that ICT is a conceptually poor indicator of technological infrastructure, it is that measuring ICT in a consistent manner over a long time period and large number of countries is difficult. Furthermore, it may be difficult to draw conclusions and policy implications from a model with such an index. One might argue that this issue could be circumvented by avoiding general ICT indices and instead, a growth model should include separate explanatory variables for each ICT dimension (i.e., one for cellular network coverage, one for AI, etc.). At the costs associated with including many RHS variables, this approach could prove beneficial in analyzing specific technologies and their effects on growth, but it would be prohibitively scope-limiting given the research objectives laid out in this paper.

Determining which products are technologically intensive is also not without issues. In fact, the exact arguments I have just laid out against ICT measures can be made against technology-intensive export performance, but using technology-intensive export performance in place of ICT draws on ideas and empirics from the technology-intensive-trade literature and therefore could lead to unique policy implications.

Technology-intensive export performance merges gracefully into technology-gap theory. The inclusion of this variable suggests that leading performers in technology-intensive exports exhibit, in some combination, high levels of absorptive capacity and high R&D sector productivity. According to technology-gap theory, countries far from the technological frontier are assumed to largely engage in imitating activities while those close to the frontier focus on innovation, but all countries engage in both to some degree. As Lall (2000) notes, learning potential is associated with manufacturing technology-intensive products, so a country manufacturing and exporting imitated technologies subjects itself to gains in R&D sector productivity. As an additional insight, technology-intensive export performance implicitly contains an element of trade openness: countries with more openness stand to exhibit better technology-intensive export performance.

4 Preliminary Analysis

4.1 Notes on Data

The period analyzed is from 1997 to 2018 using annual data by country, but some data series contain missing observations. The three R&D series are the least-complete, and are adapted from UNESCO UIS general expenditure on research and development (*GERD*)(*UNESCO Institute for Statistics (UIS)*, n.d.). In addition to total GERD, the series I use for total R&D (R), UNESCO UIS breaks GERD down into GERD by source of funds; the GERD sources with the most-complete data are *business enterprise* and *government*. Further sources of GERD include *rest-of-world*, *higher education*, and *other*, but for this analysis, only business enterprise (R_{BE}) and government (R_{GOV}) are considered. All R&D series are expressed as a percentage of GDP. Following the panel-growth-model tradition, the full time period is aggregated into five periods ($T = 5$) where each observation value is computed as the average value over the aggregation period. Averaging allows for smoothing short-term fluctuations which could skew perceptions of the long-run growth process and offers assistance for missing-data issues (Durlauf et al., 2005). The five time periods, t_1 to t_5, are comprised of the years 1997-2001, 2002-2006, 2007-2010, 2011-2014, and 2015-2018, respectively. The first two periods contain five years of data while the final three contain four because a large portion of the missing data is in the early years of the sample. By extending the first two periods by one year, more countries can be included in the analysis. I consider this acceptable because the goal of averaging is to record the general state of each country during the years contained in each period.

The countries selected for this analysis are those with a low number of missing values or a missing-data pattern that complies with the conditions I impose for the aggregation process: for each T, there are at least three observations of each variable. This criterium, when applied to each country, produces two samples. The larger of the two, Sample 1 (n=57), utilizes only R as an indicator of innovative efforts, while the smaller, Sample 2 (n=41), utilizes R_{BE} and R_{GOV}. All variables outside of R&D are identical in both samples.

Technology-intensive export performance (X) is calculated as the proportion of all technology-intensive merchandise exports in the sample for a given year. For example, if in t_2 country i exported 10 dollars of technology-intensive merchandise and the rest of the countries exported a total value of 90 dollars, $X_{i,2}$ would equal 0.1. The data used for constructing X were obtained from UNCTAD and utilize the Lall classification definition of high-technology goods (*UNCTAD STAT*, n.d.).

GDP per capita (y) is expressed in constant 2017 PPP dollars (data from *UNdata*, n.d.), and the capital investment variable (k) is expressed as gross fixed capital formation as a percentage of GDP Fagerberg (1987). The Penn World Table (*PWT* version 10.0 Feenstra et al., 2015) human capital index is used as a proxy for human capital (H).[8] Finally, the technology-gap variable is expressed as a distance-to-frontier ratio: for some country i at time t, the gap $G_{i,t}$ is $\frac{y_{i,t}}{y_{L,t}}$, where $y_{L,t}$ denotes the highest GDP per capita at time t. All data series used in this analysis contain only annual observations.

The variables defined in this section are used extensively throughout the remainder of this paper. For a single country (i) in a single *year* (τ), the variable names and definitions can be summarized as:

- $y_{i,\tau}$: GDP per capita expressed in 2017 PPP dollars;
- $X_{i,\tau}$: Technology-intensive export performance expressed as country i's percentage of all technology-intensive exports (of the respective sample) in year τ;
- $H_{i,\tau}$: Human capital expressed as the PWT version 10.0 human capital index ;

[8]This index from PWT version 10.0 considers *years of* and *returns to* education on a per-person basis.

- $k_{i,\tau}$: Capital investment expressed as gross fixed capital formation as a percentage of GDP;

- $R_{i,\tau}$: Research and development expenditure expressed as a percentage of GDP;

- $R_{BE i,\tau}$: Research and development expenditure funded by business enterprise expressed as a percentage of GDP;

- $R_{GOV i,\tau}$: Research and development expenditure funded by i's government expressed as a percentage of GDP.

Each variable is then averaged over the years contained in each time period (t) to create the final variables: $y_{i,t}$, $X_{i,t}$, $H_{i,t}$, $k_{i,t}$, $R_{i,t}$, $R_{BE i,t}$, and $R_{GOV i,t}$.

Table 1 displays the number of missing annual observations for each country and data series from 1997 to 2018 (22 years). Table 1 also indicates which sample (samples) each country belongs to. The reader is referred to the appendix for a table containing country codes and names (Table 5). Note that New Zealand (NZL) and Australia (AUS) are both missing eleven observations for each R&D variable. These two countries have missing GERD observations in the odd-numbered years, exhibiting a case where I consider the data reliable (after averaging) in spite of missing a large (fifty percent in this case) portion of the data.

Table 1: Number of Missing Observations for Each Country and Data Series

Country	Samples	R	R_{BE}	R_{GOV}	y	X	H	k
ARG	1	0	NA	NA	0	0	0	0
ARM	1	0	NA	NA	0	0	0	0
AUS	1	11	NA	NA	0	0	0	0
AUT	1 and 2	0	0	0	0	0	0	0
BEL	1 and 2	0	3	3	0	0	0	0
BGR	1 and 2	0	1	1	0	0	0	0

Table 1: Number of Missing Observations for Each Country and Data Series *(continued)*

Country	Samples	R	R_{BE}	R_{GOV}	y	X	H	k
CAN	1 and 2	0	0	0	0	0	0	0
CHN	1	0	NA	NA	0	0	0	0
COL	1	2	NA	NA	0	0	0	0
CRI	1	3	NA	NA	0	0	0	0
CYP	1 and 2	1	2	2	0	0	0	0
CZE	1 and 2	0	0	0	0	0	0	0
DEU	1 and 2	0	1	1	0	0	0	0
DNK	1 and 2	1	9	9	0	0	0	0
EGY	1	3	NA	NA	0	0	0	0
ESP	1 and 2	0	1	1	0	0	0	0
EST	1 and 2	1	2	2	0	0	0	0
FIN	1 and 2	0	1	1	0	0	0	0
FRA	1 and 2	0	1	1	0	0	0	0
GBR	1 and 2	0	1	1	0	0	0	0
GRC	1 and 2	3	6	6	0	0	0	0
HKG	1	1	NA	NA	0	0	0	0
HRV	1 and 2	2	3	3	0	0	0	0
HUN	1 and 2	0	1	1	0	0	0	0
IND	1	0	NA	NA	0	0	0	0
IRL	1 and 2	1	2	2	0	0	0	0
ISL	1 and 2	3	5	5	0	0	0	0
ISR	1 and 2	0	1	1	0	0	0	0
ITA	1	0	NA	NA	0	0	0	0
JPN	1 and 2	0	0	0	0	0	0	0
KAZ	1 and 2	0	3	3	0	0	0	0

Table 1: Number of Missing Observations for Each Country and Data Series *(continued)*

Country	Samples	R	R_{BE}	R_{GOV}	y	X	H	k
KGZ	1	0	NA	NA	0	0	0	0
KOR	1 and 2	0	0	0	0	0	0	0
LTU	1	0	NA	NA	0	0	0	0
LVA	1 and 2	0	1	1	0	0	0	0
MDG	1	4	NA	NA	0	0	0	0
MEX	1 and 2	0	0	0	0	0	0	0
MNG	1	0	NA	NA	0	0	0	0
MYS	1 and 2	8	9	9	0	0	0	0
NLD	1 and 2	0	7	7	0	0	0	0
NOR	1 and 2	2	10	10	0	0	0	0
NZL	1 and 2	11	11	11	0	0	0	0
PAN	1 and 2	1	2	1	0	0	0	0
POL	1 and 2	0	1	1	0	0	0	0
PRT	1 and 2	0	1	1	0	0	0	0
ROU	1 and 2	0	1	1	0	0	0	0
RUS	1 and 2	0	0	0	0	0	0	0
SGP	1 and 2	1	1	1	0	0	0	0
SRB	1	0	NA	NA	0	4	0	0
SVK	1 and 2	0	0	0	0	0	0	0
SVN	1 and 2	0	1	1	0	0	0	0
SWE	1 and 2	3	11	12	0	0	0	0
THA	1 and 2	4	10	12	0	0	0	0
TUR	1 and 2	1	1	1	0	0	0	0
UKR	1	0	NA	NA	0	0	0	0
URY	1 and 2	4	4	4	0	0	0	0

Table 1: Number of Missing Observations for Each Country and Data Series *(continued)*

Country	Samples	R	R_{BE}	R_{GOV}	y	X	H	k
USA	1 and 2	0	0	0	0	0	0	0

Another detail worth noting: countries that are in Sample 1 and not in Sample 2 are largely lower-income (relative to Sample 2 average income) countries, so Sample 2 contains a higher share of high-income countries. Figure 2 displays a comparison of average GDP per capita between the two samples over the five periods. Means and standard deviations of all variables used in this analysis are reported in the appendix.

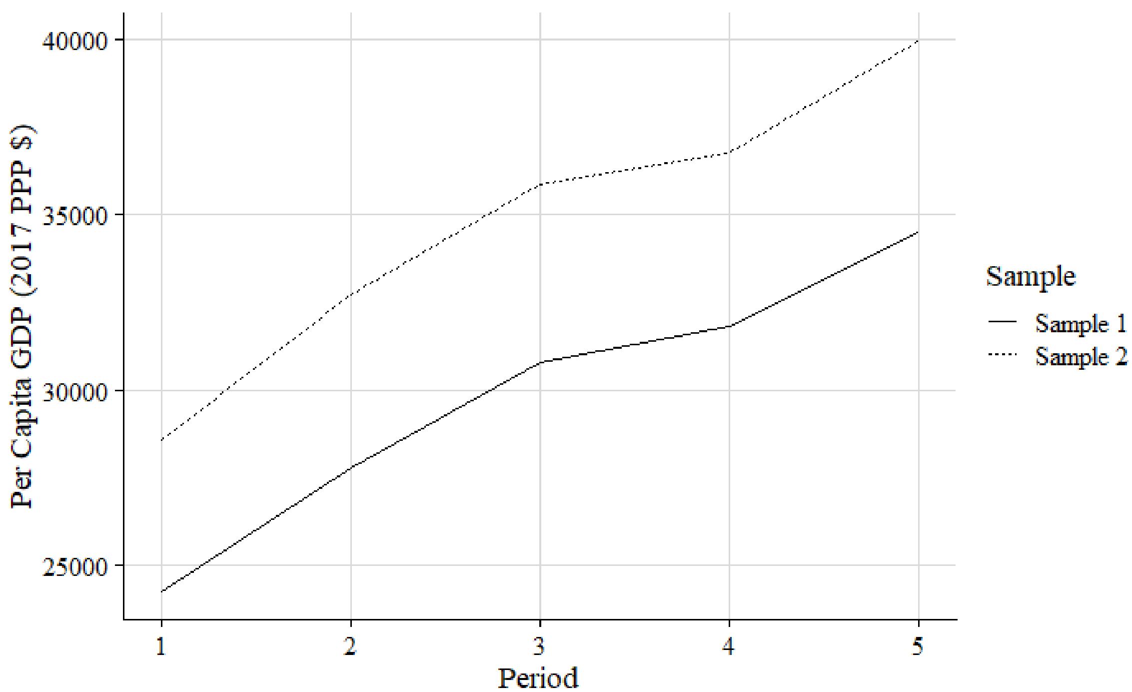

Figure 2: Mean Per Capita Income By Sample

4.2 β-Convergence in Knowledge Determinants

4.2.1 β-Convergence Regression Model

A considerable portion of the applied growth literature has investigated β-convergence in per-capita GDP across countries. In this section, the concept of β-convergence is additionally applied to the key drivers of knowledge (A): R&D expenditure (R), technology gap (G), technology-intensive export performance (X), and human capital (H). The equation of interest takes the form:

$$\log\left(\frac{A_{d,i,T}}{A_{d,i,t_1}}\right) = \alpha + \beta \log A_{d,i,t_1} + \varepsilon_{d,i}, \tag{1}$$

where i is the country index, and A_d variables are the previously mentioned drivers such that $A_d \in \{R, X, H\}$ for Sample 1 and $A_d \in \{R_{GOV}, R_{BE}, X, H\}$ for Sample 2. The time subscripts are such that A_{d,t_1} denotes the initial value of driver d, and $A_{d,T}$ is the final observed value for the period in question. ε is an error term. The coefficient of interest is β, and for convergence, its expected sign is negative. This indicates that low initial levels of A_d are associated with higher respective growth rates from t_1 to T (t_5 is equivalent to T since T denotes the final time period). This is a test of unconditional convergence; the estimated growth rate is regressed on only the natural log of its level in the first period. The results from unconditional convergence regressions provide insights pertaining to each driver's behavior from t_1 to T. Growth models like the one presented in Section 5 can be thought of as conditional convergence models, and since lagged y values play an important role in the convergence process (Durlauf et al., 2005), equation (1) is also estimated with y_i in place of $A_{d,i}$.

4.2.2 β-Convergence Results and Discussion

The model is estimated using the ordinary least squares (OLS) estimation method; the results are reported in Table 2. As expected, the coefficient estimates in the GDP per capita models are both negative and statistically significant at the 1% significance level. Interestingly, the coefficient estimates are more negative in Sample 2 than in Sample 1 for all significant variables. This provides some weak support for club convergence since, in comparison to Sample 1, Sample 2 more closely resembles a "high-income" club of countries (Aghion & Howitt, 2005). In both samples, the technology gap variable displays the strongest convergence (i.e., the most negative coefficient estimate) which suggests that countries far from the frontier are "catching up" to the leaders, ceteris paribus. Of the R&D variables, only government-funded R&D proved significant in this exercise.

Table 2: β Convergence Results

	Sample 1		Sample 2	
Variable	β Estimate	n	β Estimate	n
$\log y$	-0.2126 (0.0382)***	57	-0.3433 (0.0477)***	41
$\log X$	-0.1379 (0.0383)***	57	-0.2561 (0.0411)***	41
$\log H$	-0.1977 (0.0409)***	57	-0.2391 (0.0604)***	41
$\log R$	0.0291 (0.0811)	57		
$\log R_{BE}$			-0.1442 (0.1024)	41
$\log R_{GOV}$			-0.1718 (0.0758)**	41
$\log G$	-0.2126 (0.0382)***	57	-0.3433 (0.0477)***	41

Note: OLS estimation method; significance levels: '***' 0.01; '**' 0.05; '*' 0.1; n: number of countries used in estimation; standard errors reported in parentheses.

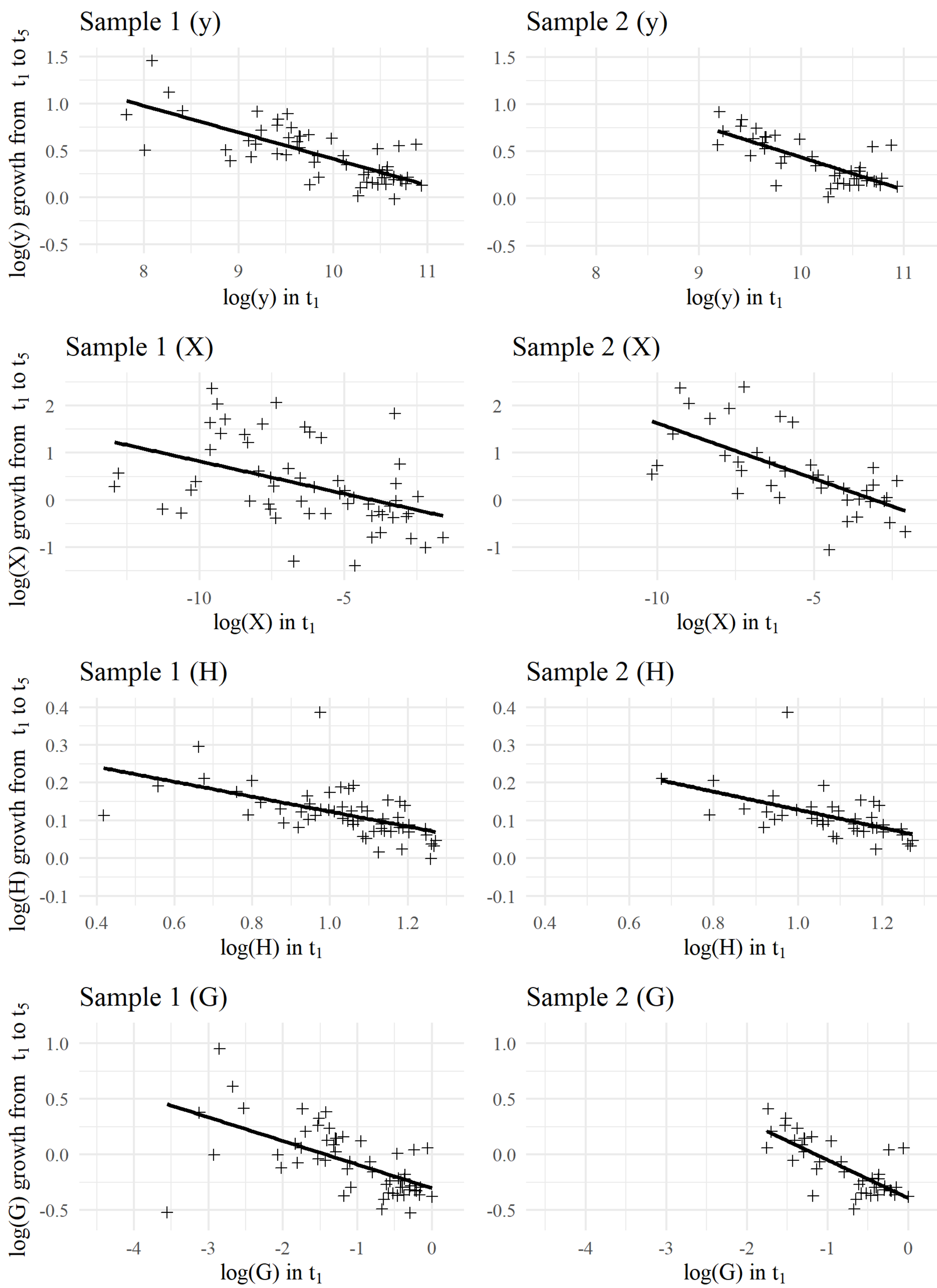

Figure 3: β-Convergence: y, X, H, G

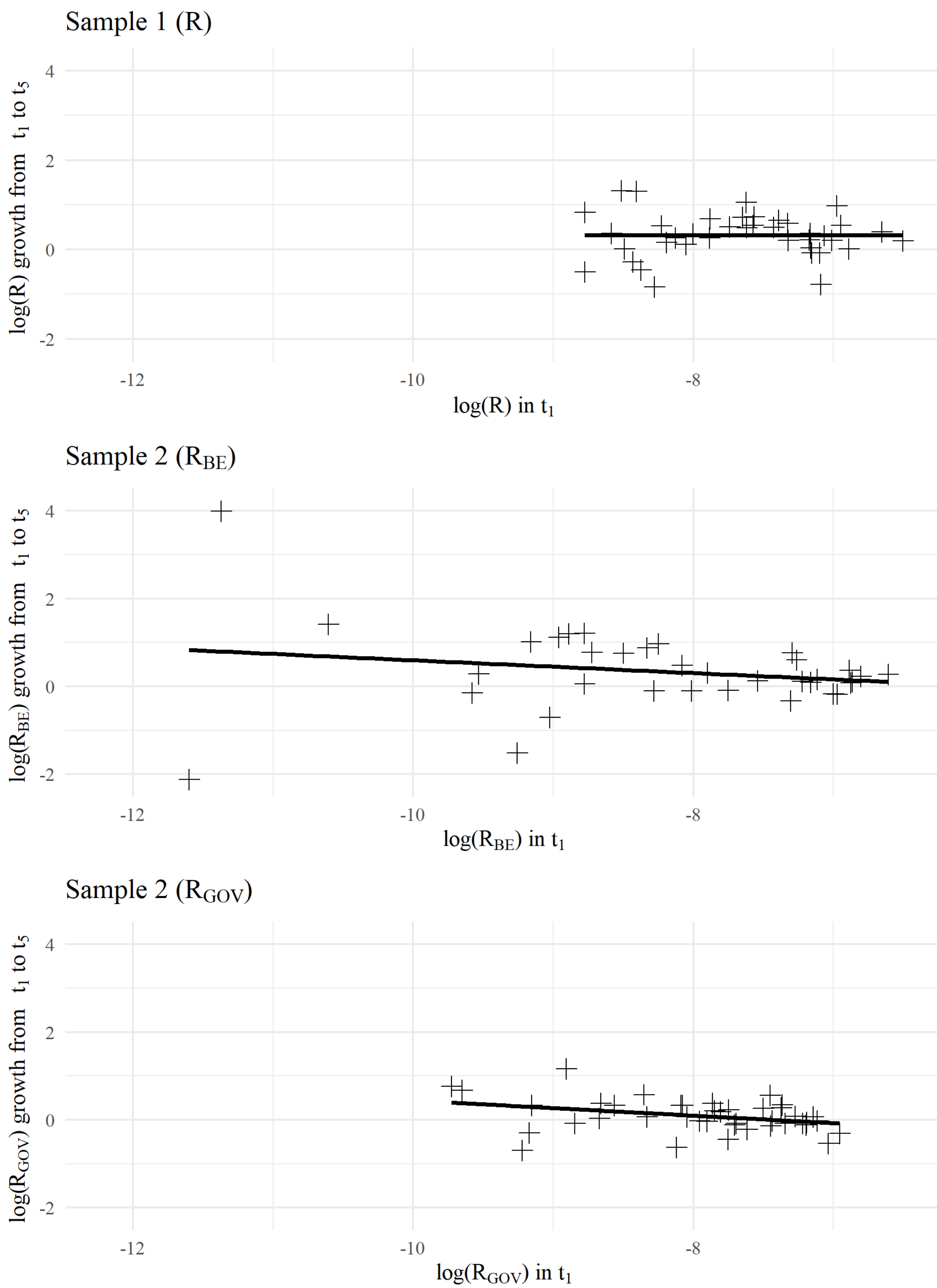

Figure 4: β-Convergence: R, R_{BE}, R_{GOV}

Figures 3 and 4 echo the results reported in Table 2. In Figure 3, GDP per capita, technology-intensive export performance, human capital, and technology gap all display visibly negative slope coefficients. Given that the plots for Sample 1 and Sample 2 have identical scales, differences between the two samples can be observed along the x-axis for the plots pertaining to y, X, H, and G in Figure 3. For each of these variables, it can be seen that many of the countries with low initial values (i.e., low values of $\log A_{d,i,t_1}$ along the x-axis) in Sample 1 are absent in Sample 2. In Figure 4, it is apparent that total R&D (R) does not exhibit a discernible pattern of unconditional β-convergence. Business-enterprise-funded R&D (R_{BE}) exhibits a downward sloping regression line, but the countries are highly-dispersed which produces an insignificant β estimate. Government-funded R&D (R_{GOV}) shows more uniformity than R_{BE}, and exhibits a significant pattern of convergence within the Sample 2 countries.

5 Empirical Model

5.1 Model Development

Consider the case for a single country. We begin with the Cobb-Douglas production function,

$$Y = AK^{\alpha}L^{1-\alpha}. \tag{2}$$

Dividing both sides by L yields

$$\frac{Y}{L} = A\frac{K^{\alpha}L^{1-\alpha}}{L^{\alpha}L^{1-\alpha}}, \tag{3}$$

which simplifies to

$$\frac{Y}{L} = A\left(\frac{K}{L}\right)^{\alpha}. \tag{4}$$

Using lowercase notation for per-worker variables and taking logs produces:

$$\log y = \log A + \alpha \log k, \tag{5}$$

where the knowledge term depends upon knowledge creation (Ω) and knowledge imitation (Φ) as in equation (6) (e.g., Castellacci (2011); Acemoglu et al. (2006); Fagerberg (1987)). $\log A$ is defined as:

$$\log A = \log \Omega + \log \Phi, \tag{6}$$

where Ω and Φ are defined (equations (7) and (8), respectively) in accordance with Castellacci (2011).

$$\Omega = R^{\gamma}\theta, \tag{7}$$

$$\Phi = G^{\beta}\delta, \tag{8}$$

where R represents innovative efforts toward knowledge creation, and θ is the productivity of the research and development sector as it relates to the knowledge-creation process. Equation (8) reflects the core concept of gap-based models: the potential for knowledge imitation arises from a country's position relative to the leader (i.e., technological distance to frontier), and its absorptive capacity (δ) represents how effectively this gap is exploited. It follows that the leader (the singular country for which the distance is zero) has no opportunity for imitation, so any contribution to A is brought about purely through knowledge creation via innovation. Both knowledge creation and imitation are determined by the dynamics of technological infrastructures (X) and human capital (H). As has been frequently noted in the existing literature, highly-developed technological infrastructure will struggle to contribute to a country's knowledge stock without a complementarily high level of human capital and vice versa.

Again following Castellacci (2011), endogenizing θ and δ yields equations (9) and

(10), respectively:

$$\theta = X^{\theta_1} H^{\theta_2} \tag{9}$$

$$\delta = X^{\delta_1} H^{\delta_2}. \tag{10}$$

By substituting and then simplifying the right-hand side, $\log A$ can be expressed as[9]

$$\log A = \log \underbrace{(R^{\gamma} X^{\theta_1} H^{\theta_2})}_{\Omega} + \log \underbrace{(G^{\beta} X^{\delta_1} H^{\delta_2})}_{\Phi} \tag{11a}$$

$$\log A = \gamma \log R + \beta \log G + (\theta_1 + \delta_1) \log X + (\theta_2 + \delta_2) \log H. \tag{11b}$$

Substituting (11b) into the per-worker aggregate production function (equation 5), including time subscripts, and utilizing the definition of G as defined in Section 4.1, $G_{i,t-1} = \frac{y_{i,t-1}}{y_{L,t-1}}$ yields the equation,

$$\log y_{i,t} = \beta \log y_{i,t-1} - \beta \log y_{L,t-1} + \gamma \log R_{i,t} + \pi \log X_{i,t} + \rho \log H_{i,t} + \alpha \log k_{i,t}. \tag{12}$$

At this juncture, it should be noted that the decomposition of θ and δ—as in equations (9) and (10)—is conceptually intriguing, but empirically immeasurable with this specification. As the literature suggests, X and H play crucial roles in both the knowledge creation and imitation processes, but this model does not acknowledge a distinction. The terms $(\theta_1 + \delta_1)$ and $(\theta_2 + \delta_2)$ are represented by π and ρ in equation (12), respectively, but moving forward, it can be assumed that π and ρ are comprised of the two elements impacting both the knowledge creation and knowledge imitation processes.

Introducing and defining the composite error term $u_{i,t}$ produces the dynamic

[9] Equation (11a) implies $A = R^{\gamma} X^{(\theta_1+\delta_1)} H^{(\theta_2+\delta_2)} G^{\beta}$.

panel model:

$$\begin{gathered}\log y_{i,t} = \beta \log y_{i,t-1} + \pi \log X_{i,t} + \rho \log H_{i,t} + \alpha \log k_{i,t} + \gamma \log R_{i,t} + u_{i,t}, \\ u_{i,t} = \eta_i + \varepsilon_{i,t}.\end{gathered} \tag{13}$$

The composite error term $u_{i,t}$ is separated into two components: country-specific effects, η_i, and the idiosyncratic component, $\varepsilon_{i,t}$. Combining (13) with this definition for $u_{i,t}$ produces the single equation form:

$$\log y_{i,t} = \beta \log y_{i,t-1} + \pi \log X_{i,t} + \rho \log H_{i,t} + \alpha \log k_{i,t} + \gamma \log R_{i,t} + \eta_i + \varepsilon_{i,t}. \tag{14}$$

The leader country's log income ($\log y_{L,t-1}$) is invariant across countries, so in equations (13) and (14), $\beta \log y_{L,t-1}$ is omitted and will be accounted for by a set of time dummies in estimation. The time dummies will also account for any other shocks affecting all countries (e.g., a global recession).

First differencing equation (14), and utilizing Δ as the first difference operator, eliminates the unobserved country-specific heterogeneity η_i (Arellano & Bond, 1991). Equation (15) is specified as a dynamic panel model including one (strictly endogenous) lag of the dependent variable, $\log y_i$. The differenced equation is as follows:

$$\begin{gathered}\Delta \log y_{i,t} = (1+\beta)\Delta \log y_{i,t-1} + \pi\Delta \log X_{i,t} + \rho\Delta \log H_{i,t} + \alpha\Delta \log k_{i,t} \\ +\gamma\Delta \log R_{i,t} + \Delta\varepsilon_{i,t}.\end{gathered} \tag{15}$$

As noted in Durlauf et al. (2005), most panel-data growth models assume, conditional on a few variables, countries converge to parallel balanced growth paths—equation (15) makes this assumption. A common practice among practitioners is to express the lagged log income coefficient as $(1+\beta)$ which only changes the coefficient's interpretation and expectation (Castellacci, 2011; Durlauf et al., 2005). If convergence is expected, most β-convergence analyses expect the sign of the coefficient on lagged income (often lagged log income) to be negative (see Section 4.3 for an example). The coefficient $(1+\beta)$ in equation (15) is expected to be positive and less than one if convergence is present. Equations (13) and (14) (expressed in levels), and their first-differenced counterpart, equation (15), are the equations considered for estimating "Model 1" in Section 5.3. For the sample with R&D by source of funds (Sample 2), another dynamic panel model can be written as follows:

$$\begin{gathered} \log y_{i,t} = \beta \log y_{i,t-1} + \pi \log X_{i,t} + \rho \log H_{i,t} + \alpha \log k_{i,t} \\ +\gamma_{BE} \log R_{BE\,i,t} + \gamma_{GOV} \log R_{GOV\,i,t} + u_{i,t}, \\ u_{i,t} = \eta_i + \varepsilon_{i,t}. \end{gathered} \tag{16}$$

Again utilizing the definition of $u_{i,t}$, the singe equation form can be expressed as:

$$\begin{gathered} \log y_{i,t} = \beta \log y_{i,t-1} + \pi \log X_{i,t} + \rho \log H_{i,t} + \alpha \log k_{i,t} \\ +\gamma_{BE} \log R_{BE\,i,t} + \gamma_{GOV} \log R_{GOV\,i,t} + \eta_i + \varepsilon i, t. \end{gathered} \tag{17}$$

First differencing (17) yields:

$$\begin{gathered} \Delta \log y_{i,t} = (1+\beta)\Delta \log y_{i,t-1} + \pi\Delta \log X_{i,t} + \rho\Delta \log H_{i,t} + \alpha\Delta \log k_{i,t} \\ +\gamma_{BE}\Delta \log R_{BE\,i,t} + \gamma_{GOV}\Delta \log R_{GOV\,i,t} + \Delta\varepsilon_{i,t}. \end{gathered} \tag{18}$$

In equations (16), (17), and (18), R_{GOV} and γ_{GOV} correspond to government-funded R&D expenditure, and R_{BE} and γ_{BE} correspond to R&D funded by business enterprise. Just as in the equations for Model 1, η_i is eliminated after first differencing (17) to produce (18). Equations (16)-(18) are used when estimating "Model 2" in sections 5.2 and 5.3.

5.2 GMM Estimation Methodology

The linear dynamic panel models presented in the previous section account for dynamics and unobserved country-specific heterogeneity (Durlauf et al., 2005; Fritsch et al., 2021b). Given the obvious endogeneity, estimation of these models with OLS is inconsistent since the first difference of the lagged dependent variable ($\Delta \log y_{i,t-1}$) and first difference of the idiosyncratic component ($\Delta\varepsilon_{i,t}$) are not orthogonal (Fritsch et al., 2021b). The most popular approaches for estimating dynamic panel models which can overcome the endogeneity issue are the generalized method of moments (*GMM*) family of estimators, the two most prevalent being difference GMM estimator and the system GMM estimator (Arellano & Bond, 1991; Arellano & Bover, 1995).

For simplicity of the following discussion about model assumptions and moment conditions, consider an example dynamic panel model expressed in levels and first differences:

$$\begin{aligned}
\text{In levels:} \quad y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t} + u_{i,t}, \qquad i, \ldots, N, \quad t = 1, \ldots, T,\\
u_{i,t} = \eta_i + \varepsilon_{i,t},\\
y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t} + \eta_i + \varepsilon_{i,t}\\
\text{In first differences:} \quad \Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \beta \Delta x_{i,t} + \Delta\varepsilon_{i,t}.
\end{aligned} \tag{19}$$

This model contains the first lag of the dependent variable and one additional RHS variable ($x_{i,t}$) which is *predetermined* in this exposition. Coefficients α and β are parameters; $u_{i,t}$, η_i, and $\varepsilon_{i,t}$ retain their definitions from Section 5.1.

The following procedure and explanation follows Fritsch et al. (2021b)—a vignette for the `R` package `pdymnc` (Fritsch et al., 2021a; R Core Team, 2021). In all estimations, $\log y_{i,t-1}$ is considered strictly endogenous while $\log X_{i,t}$, $\log H_{i,t}$, $\log k_{i,t}$, and $\log R_{i,t}$ (in Model 2, $\log R_{BEi,t}$ and $\log R_{GOV\,i,t}$ replace $\log R_{i,t}$) are considered predetermined (weakly endogenous) to allow for potential feedback from GDP per capita to all other variables (Castellacci, 2011; Levine et al., 2000).

As a brief overview of the GMM estimators employed in this section: in GMM estimation, parameter estimates can be produced by deriving moment conditions—which may be linear or nonlinear in the model parameters—from the model assumptions (Fritsch, 2019). Arellano & Bond (1991) suggest using lags of the dependent variable in levels as instruments for the first-differenced variable. The idea is that $y_{i,t-2}$, $y_{i,t-3}$, and deeper lags of $y_{i,t}$ are correlated with $\Delta y_{i,t-1}$ (ideally), but are not correlated with the first-differenced idiosyncratic error component, $\Delta\varepsilon_{i,t}$.

The approach developed in Arellano & Bond (1991) is often referred to as "difference GMM" because only the first-differenced equation is used for estimation, with instruments in levels. Blundell & Bond (1998) show that if we assume $E\left(\Delta y_{i,1} \cdot \eta_i\right) = 0$, the first differences become suitable instruments for the levels. In system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998), both the levels and differenced equations are instrumented and estimated, independently and simultaneously (Roodman, 2009). Both difference GMM and system GMM were created for short, wide (small T, large n) panels, a common panel-data structure for economic growth analyses.

The standard model assumptions (STD), which are assumed to hold in the empirical growth literature are as follows (generally following notation from Fritsch et al., 2021b):[10]

$$E\left(\eta_i\right) = 0, \qquad i = 1, \ldots, n, \tag{STD.A1}$$

$$E\left(\varepsilon_{i,t}\right) = 0, \qquad i = 1, \ldots, n, \quad t = 2, \ldots, T, \tag{STD.A2}$$

$$E\left(\varepsilon_{i,t} \cdot \eta_i\right) = 0, \qquad i = 1, \ldots, n, \quad t = 2, \ldots, T, \tag{STD.A3}$$

$$E\left(\varepsilon_{i,t} \cdot \varepsilon_{i,s}\right) = 0, \qquad i = 1, \ldots, n, \quad t \neq s, \tag{STD.A4}$$

$$E\left(y_{i,1} \cdot \varepsilon_{i,t}\right) = 0, \qquad i = 1, \ldots, n, \quad t = 2, \ldots, T, \tag{STD.A5}$$

where T is fixed and $n \longrightarrow \infty$.

All STD are henceforth assumed to hold.

Under STD, we have the following moment conditions proposed by Holtz-Eakin et al. (1988) (*HNR*):[11]

$$E\left(y_{i,s} \cdot \Delta u_{i,t}\right) = 0, \qquad t = 3, \ldots, T, \quad s = 1, \ldots, t-2. \tag{HNR.MC1}$$

As noted in Roodman (2009), (HNR.MC1) provides $(T-1)(T-2)/2$ moment conditions and therefore (HNR.MC1) is quadratic in T. This could contribute to the instrument proliferation problem, where high instrument counts weaken specification tests. For predetermined $x_{i,t}$, we also have the moment conditions (Fritsch et al., 2021b),

$$E\left(x_{i,s} \cdot \Delta u_{i,t}\right) = 0, \qquad t = 3, \ldots, T, \quad s = 1, \ldots, t-1. \tag{HNR.MC2}$$

Although quadratic in T, HNR moment conditions are linear in α and β and are referred to as *linear moment conditions* (see Fritsch, 2019 for more detail). When HNR moment conditions are employed alone, we have a difference GMM estimator.

[10]Equation tags ending in ".A" denote assumptions.
[11]Equation tags ending in ".MC" denote moment conditions.

As an extension to STD assumptions, additional moment conditions can be derived from the commonly-assumed "constant correlated effects" (*CCE*) assumption (Arellano & Bover, 1995; Blundell & Bond, 1998):

$$E\left(\Delta y_{i,t} \cdot \eta_i\right) = 0, \qquad i = 1, \ldots, n. \tag{CCE.A}$$

Under CCE, Arellano & Bover (1995) (*ABOV*) propose the moment conditions

$$E\left(\Delta y_{i,t-1} \cdot u_{i,t}\right) = 0, \qquad t = 3, \ldots, T, \tag{ABOV.MC1}$$

for endogenous y, and

$$E\left(\Delta x_{i,\nu} \cdot u_{i,t}\right) = 0, \qquad \nu = t, \quad t = 2, \ldots, T, \tag{ABOV.MC2}$$

for predetermined x. As with HNR, ABOV moment conditions are linear in parameters.

Although commonly assumed to hold, the CCE assumption is often questionable, so I approach the ABOV moment conditions with caution. If CCE is in doubt, the *nonlinear moment conditions* (quadratic in parameters, see Fritsch, 2019) proposed by Ahn & Schmidt (1995) (*AS*) may be employed. Under only the standard assumptions (STD), we have the nonlinear moment conditions (Ahn & Schmidt, 1995; Fritsch et al., 2021b),

$$E\left(u_{i,T} \cdot \Delta u_{i,t-1}\right) = 0, \qquad t = 4, \ldots, T. \tag{AS.MC}$$

If the data generation process for $y_{i,t}$ is highly persistent (or close to a random walk process), the lagged levels ($y_{i,t}$) are poorly correlated with—and thus weak instruments for—the first differences ($\Delta y_{i,t-1}$) (Blundell & Bond, 1998, 2000).[12] In this case, difference GMM (in the example above and moving forward, employing HNR moment conditions alone) may fail to identify the α parameter due to its known

[12] Blundell & Bond (2000) note that persistence is often the case with economic panel data.

imprecision and downward finite sample bias (Arellano & Bond, 1991; Blundell & Bond, 1998, 2000). Extending the model assumptions to include CCE, and employing the ABOV moment conditions in addition to HNR, produces a system GMM estimator. Blundell & Bond (2000) showed that system GMM exhibits efficiency and precision gains over the difference GMM estimator, especially when the lagged parameter (α) is near unity. As a robustness check of the CCE assumption, combining HNR and AS (nonlinear) moment conditions may also identify the lagged parameter α under only STD assumptions. If the estimations of α are similar between HNR+ABOV and HNR+AS and the model is properly specified, then there is evidence that the CCE assumption holds (Fritsch et al., 2021b).

5.3 Results and Discussion

The tables in this section present the results from the GMM estimation and include coefficient estimates and their associated standard errors, number of instruments generated, and specification tests. The "J-Hansen", "AR(2)", and "Wald" rows of the tables correspond to the Hansen J-test against the null hypothesis that overidentification restrictions are valid, the Arellano and Bond (1991) test against the null of no second-order serial correlation, and a Wald test of the null hypothesis that all parameters are jointly zero, respectively Fritsch et al. (2021a). Following convention, the Windmeijer (2005) two-step GMM correction is employed in all standard errors reported. Roodman (2009) notes that high instrument counts weaken the Hansen J-test of overidentification restrictions. Following Roodman's advice, the number of lags used as instruments has been limited where possible to curb the instrument proliferation issue and its consequences. Instrument counts reported in the following tables reflect these imposed limitations.

Table 3 presents the GMM estimation results of Model 1—equations (13), (14), and (15)—with Sample 1 panel data (57 countries, 5 periods). Utilizing HNR moment conditions under STD (column *a*), the model is misspecified at the 5% significance level due to a lack of overidentification restrictions indicated by the Hansen J-test. The specification tests suggest no evidence of inadequate specification when the HNR moment conditions are extended to include the ABOV moment conditions (column *b*) or AS moment conditions (column *c*). Estimating Model 1 with HNR+ABOV moment conditions—assuming constant correlated effects—results in lagged GDP per capita, human capital, and investment having a positive and significant effect on GDP per capita growth, while the technology-intensive export performance and total R&D coefficients are found to be insignificant at any reasonable significance level. As a check of the CCE assumption, column *c* presents the results from employing HNR and AS moment conditions and only assuming STD hold. The lagged parameter $(1 + \beta)$ in column *c* differs convincingly from column b, and casts doubt upon the CCE assumption (Fritsch et al., 2021b). Therefore, I consider the results produced by HNR+AS moment conditions to be the most robust and reliable.

Table 3: Model 1 (Sample 1) Results

		HNR	**HNR+ABOV**	**HNR+AS**
	Parameter	*(a)*	*(b)*	*(c)*
Coefficient Estimates				
$\log y_{t-1}$	$1+\beta$	0.5528	0.8839	0.6142
		(0.101)***	(0.024)***	(0.098)***
$\log X_t$	π	0.065	0.0049	0.0527
		(0.031)**	(0.011)	(0.029)*
$\log H_t$	ρ	0.6884	0.5295	0.7964
		(0.414)*	(0.16)***	(0.447)*
$\log k_t$	α	0.2538	0.2667	0.253
		(0.087)***	(0.038)***	(0.066)***
$\log R_t$	γ	-0.0355	0.0078	-0.0315
		(0.034)	(0.021)	(0.027)
Specification Tests				
	J-Hansen	0.0371**	0.5256	0.1016
p values	AR(2)	0.1183	0.1303	0.4439
	Wald	<0.001***	<0.001***	<0.001***
	Instruments	30	58	46
	n	57	57	57
	T	5	5	5

Note: Time dummies included in all estimations; Standard errors in parentheses—all standard errors are adjusted via the Windmeijer (2005) correction; Significance levels: '***' 0.01, '**' 0.05, '*' 0.1; All estimators are two-step GMM estimators.

Column c of Table 3 indicates that human capital has the largest positive effect on GDP per capita growth—significant at the 10% level. Technology-intensive export has a small, positive effect on growth which, broadly speaking, aligns with the conclusions from Daniels (1999). The investment parameter's (α) estimate indicates that investment is an important contributor to the growth process in the twenty-first century. Research and development, as defined in Section 4.1, proves insignificant in columns b and c, aligning with the β-convergence results found in Section 4.3. In the presence of technology-intensive export performance, human capital, and capital investment, I find that total R&D (expressed as a percentage of GDP) plays an insignificant role in the economic growth process for the countries in Sample 1.

Table 4 presents the GMM estimation results of Model 2—equations (16), (17), and (18)—with Sample 2 panel data (41 countries, 5 periods). Employing HNR moment conditions alone, the model specification is somewhat questionable given the AR(2) test results; the same can be said for HNR+AS moment conditions. However, using a significance level of 10%, all specification tests in columns a and c are passed. These columns should be taken with a grain of salt on their own because the specification testing results are suboptimal, but more information is revealed when a and c are viewed in contrast to b. It is again apparent that the lagged parameter estimates in columns b and c differ convincingly, and therefore the constant correlated effects assumption is in doubt. I consider column c to be the most robust and reliable estimation results of the three.

Table 4: Model 2 (Sample 2) Results

		HNR	**HNR+ABOV**	**HNR+AS**
	Parameter	a	b	c
Coefficient Estimates				
$\log y_{t-1}$	$1+\beta$	0.3791	0.8933	0.4151
		(0.133)***	(0.017)***	(0.06)***
$\log X_t$	π	0.1101	-0.0093	0.0971
		(0.043)**	(0.005)*	(0.021)***
$\log H_t$	ρ	0.5571	0.2852	0.5156
		(0.477)	(0.111)**	(0.22)**
$\log k_t$	α	0.2758	0.2835	0.2667
		(0.092)***	(0.042)***	(0.058)***
$\log R_{BEt}$	γ_{BE}	-0.0142	0.0048	-0.0192
		(0.03)	(0.008)	(0.015)
$\log R_{GOVt}$	γ_{GOV}	0.0733	-0.003	0.0451
		(0.05)	(0.018)	(0.049)
Specification Tests				
	J-Hansen	0.2704	0.957	0.8016
p values	AR(2)	0.083 *	0.4694	0.0823*
	Wald	<0.001***	<0.001***	<0.001***
	Instruments	36	56	55
	n	41	41	41
	T	5	5	5

Note: Time dummies included in all estimations; Standard errors in parentheses—all standard errors are adjusted via the Windmeijer (2005) correction; Significance levels: '***' 0.01, '**' 0.05, '*' 0.1; All estimators are two-step GMM estimators.

In Table 4, the technology-intensive export performance factor is shown to have a positive effect on growth, with almost twice the magnitude as in Table 3. Again, in Model 2, human capital has the most pronounced positive effect on GDP per capita growth, and the estimation for the investment parameter α is nearly identical to the results from Model 1. Furthermore, the R&D variables are found to be insignificant at any reasonable significance level.

6 Summary, Implications, and Limitations

Results of analyzing the economic growth models presented in this paper suggest that human capital is a strong determinant of economic growth. To a lesser degree than human capital, investment and technology-intensive export performance also have positive effects on economic growth. Surprisingly, the research and development variables are insignificant in both models presented, regardless of the moment conditions employed in estimation. Over the years 1997-2018, I find that GDP per capita, human capital, technology-intensive export performance, and technology gaps display patterns of unconditional β-convergence: countries with low levels of each knowledge determinant in the first period (t_1: 1997-2001) exhibit higher growth rates from t_1 to T (T: 2015-2018) relative to countries with high levels in t_1. Additionally, of the three R&D variables presented in this paper (total, government-funded, and business-enterprise-funded), only government-funded R&D expenditure exhibits a pattern of convergence among a sample of 41 countries from 1997 to 2018.

Of the findings in this paper, the results regarding technology-intensive export performance and human capital may be of greatest interest to policymakers. Lall (2000) suggests that the production of technology-intensive merchandise yields *learning* spillover effects. It follows that the skills and knowledge gained from this production process contribute to human capital. The results of this paper suggest that this feedback loop played an important role in economic growth. If the goal of a policymaker is to increase her nation's economic growth, this paper suggests that policies aimed at bolstering technology-intensive export performance and human capital may serve her economy well.

This study was greatly limited by data availability. The results, conclusions, and implications drawn from this paper can only be considered to hold for the countries included in the two samples, respectively. Furthermore, all empirical results must be considered based on the stated definitions for each variable. Given the sparse nature of each R&D data series, I was not able to create five equal time periods without drastically reducing the number of countries included in the analysis. The first two periods (t_1 and t_2) each span six years, while the final three periods (t_1, t_2, and t_3) each span five years.

Further research on this topic may include alternative variable definitions, alternative model specifications, or utilizing external instruments in estimation (the use of external instruments is permitted by GMM and implemented in many software applications). Applying this paper's methodology to a smaller set of countries with common features (common geography, members of a trade organization, etc.) may provide helpful insights.

Appendix

Table 5: Sample 1 Means and Standard Deviations

Period	y	X	H	k	G	R
1	24229.1	0.02	2.85	22.61	0.43167	0.00104
	(15071.25967)	(0.03408)	(0.46552)	(4.86933)	(0.26851)	(0.00088)
2	27785.55	0.02	2.95	23.18	0.43941	0.00114
	(16354.20147)	(0.02985)	(0.45897)	(4.5063)	(0.25863)	(0.00096)
3	30774.27	0.02	3.03	24.61	0.41989	0.00125
	(16704.1046)	(0.03264)	(0.45096)	(5.04519)	(0.22791)	(0.00101)
4	31816.52	0.02	3.11	22.52	0.37679	0.00132
	(16813.45317)	(0.03667)	(0.44265)	(5.87374)	(0.19912)	(0.00103)
5	34516.03	0.02	3.19	22.22	0.37002	0.00135
	(18248.64101)	(0.03748)	(0.44482)	(5.34072)	(0.19563)	(0.00107)

Note: Standard deviations in parentheses.

Table 6: Sample 2 Means and Standard Deviations

Period	y	X	H	k	G	R_{BE}	R_{GOV}
1	28553.68	0.02	2.96	23.34	0.50871	0.00067	0.00043
	(13554.81586)	(0.04345)	(0.38965)	(4.34856)	(0.24149)	(0.00064)	(0.00025)
2	32700.08	0.02	3.06	23.26	0.51713	0.00073	0.00045
	(14451.04174)	(0.03725)	(0.38803)	(3.64355)	(0.22853)	(0.00069)	(0.00025)
3	35851.55	0.02	3.14	23.76	0.48916	0.00079	0.00049
	(14397.89343)	(0.03567)	(0.37856)	(3.18467)	(0.19645)	(0.00071)	(0.00025)
4	36782.75	0.02	3.22	21.9	0.4356	0.00081	0.00049
	(14554.18317)	(0.03557)	(0.36871)	(4.35594)	(0.17236)	(0.00074)	(0.00025)
5	39990.04	0.02	3.3	22.35	0.4287	0.00084	0.00046
	(15941.19197)	(0.03553)	(0.37282)	(4.54009)	(0.17089)	(0.00075)	(0.00025)

Note: Standard deviations in parentheses.

Summary Statistics by Income Classification

The following tables display summary statistics based on World Bank's 2022 income classification (*World Bank*, n.d.). The classification groups and their respective abbreviations are as follows:

- LI: Low income
- LMI: Lower-middle income
- UMI: Upper-middle income
- HI: High income

Table 7: Number of Countries by World Bank Income Classification

	WB Classification	Sample 1	Sample 2
1	HI	36	32
4	UMI	15	9
3	LMI	5	0
2	LI	1	0

Note: Number of countries with the given 2022 income classification in each respective sample.

Table 8: Country Codes and Income Classification

Code	Name	Classification	Code	Name	Classification
ARG	Argentina	UMI	KOR	Korea, Rep.	HI
ARM	Armenia	UMI	KGZ	Kyrgyz Republic	LMI
AUS	Australia	HI	LVA	Latvia	HI
AUT	Austria	HI	LTU	Lithuania	HI
BEL	Belgium	HI	MDG	Madagascar	LI
BGR	Bulgaria	UMI	MYS	Malaysia	UMI
CAN	Canada	HI	MEX	Mexico	UMI
CHN	China	UMI	MNG	Mongolia	LMI
COL	Colombia	UMI	NLD	Netherlands	HI
CRI	Costa Rica	UMI	NZL	New Zealand	HI
HRV	Croatia	HI	NOR	Norway	HI
CYP	Cyprus	HI	PAN	Panama	UMI
CZE	Czech Republic	HI	POL	Poland	HI
DNK	Denmark	HI	PRT	Portugal	HI
EGY	Egypt, Arab Rep.	LMI	ROU	Romania	UMI
EST	Estonia	HI	RUS	Russian Federation	UMI
FIN	Finland	HI	SRB	Serbia	UMI
FRA	France	HI	SGP	Singapore	HI
DEU	Germany	HI	SVK	Slovak Republic	HI
GRC	Greece	HI	SVN	Slovenia	HI
HKG	Hong Kong SAR, China	HI	ESP	Spain	HI
HUN	Hungary	HI	SWE	Sweden	HI
ISL	Iceland	HI	THA	Thailand	UMI
IND	India	LMI	TUR	Turkey	UMI
IRL	Ireland	HI	UKR	Ukraine	LMI
ISR	Israel	HI	GBR	United Kingdom	HI
ITA	Italy	HI	USA	United States	HI
JPN	Japan	HI	URY	Uruguay	HI
KAZ	Kazakhstan	UMI			

Note: Classification: 2022 World Bank country classification by income

Table 9: Sample 1 Means and Standard Deviations by WB Income Classification

Period	Classification	y	X	H	k	G	R
1	**HI**	32804.84352	0.02415	3.04783	23.92818	0.58445	0.00142
		(11958.52517)	(0.04056)	(0.33944)	(4.13403)	(0.21305)	(9e-04)
	UMI	11601.95023	0.00854	2.59711	20.46784	0.2067	4e-04
		(4415.22864)	(0.01442)	(0.35849)	(5.31438)	(0.07866)	(0.00022)
	LMI	4890.99477	0.00046	2.43219	21.66557	0.08714	0.00045
		(2277.0861)	(0.00073)	(0.56791)	(4.75821)	(0.04057)	(0.00035)
	LI	1600.07963	0	1.51844	12.22631	0.02851	0.00015
2	**HI**	37327.07202	0.02215	3.13877	23.4562	0.59031	0.00154
		(12496.30048)	(0.03169)	(0.33429)	(3.73985)	(0.19762)	(0.00097)
	UMI	13863.58099	0.01329	2.70989	23.0049	0.21924	0.00045
		(4217.95917)	(0.02924)	(0.35946)	(5.66403)	(0.0667)	(0.00033)
	LMI	6105.55881	7e-04	2.54512	22.92701	0.09656	0.00049
		(3098.57302)	(0.00115)	(0.55476)	(6.28457)	(0.049)	(0.00034)
	LI	1520.19921	1e-05	1.57932	17.09684	0.02404	0.00022
3	**HI**	40538.40146	0.02031	3.22092	23.16453	0.55311	0.00168
		(12455.38598)	(0.02791)	(0.32402)	(2.91143)	(0.16994)	(0.00101)
	UMI	17054.35581	0.01749	2.78638	26.59353	0.23269	0.00054
		(4779.97057)	(0.04664)	(0.34683)	(7.2674)	(0.06522)	(0.00045)
	LMI	7462.98835	0.00129	2.65733	27.6096	0.10183	0.00049
		(3644.03088)	(0.00232)	(0.53887)	(6.29558)	(0.04972)	(0.00031)
	LI	1620.38743	1e-05	1.62595	31.79162	0.02211	0.00013
4	**HI**	41215.87868	0.01885	3.29771	21.04528	0.4881	0.00177
		(13227.98545)	(0.02643)	(0.31488)	(3.76909)	(0.15665)	(0.001)
	UMI	19090.57718	0.02078	2.8577	24.73944	0.22608	0.00061
		(5216.25848)	(0.05918)	(0.32488)	(7.20467)	(0.06177)	(0.00055)
	LMI	8374.9945	0.00191	2.76595	26.68325	0.09918	0.00048
		(3583.67663)	(0.00361)	(0.52913)	(10.82001)	(0.04244)	(0.00028)
	LI	1536.49517	1e-05	1.66419	21.52118	0.0182	6e-05
5	**HI**	44544.24658	0.01877	3.38114	21.55583	0.47752	0.0018
		(14670.21486)	(0.02699)	(0.32318)	(3.74367)	(0.15727)	(0.00105)
	UMI	21152.97008	0.02104	2.93531	23.90934	0.22676	0.00067
		(5558.49434)	(0.06054)	(0.30501)	(7.59039)	(0.05959)	(0.00061)
	LMI	8989.69229	0.00178	2.87841	22.47741	0.09637	0.00043
		(3232.85124)	(0.00354)	(0.53142)	(7.62402)	(0.03466)	(0.00032)
	LI	1577.54016	0	1.70032	19.27704	0.01691	1e-05

Note: Standard deviations in parentheses; LI has one observation, so no standard deviation is reported; Classification: 2022 World Bank Classification by income.

Table 10: Sample 2 Means and Standard Deviations by WB Income Classification

Period	Classification	y	X	H	k	G	R_{BE}	R_{GOV}
1	**HI**	32909.26348	0.02814	3.05827	23.96074	23968.96288	0.00082	5e-04
		(12082.56981)	(0.04796)	(0.33957)	(4.23935)	(11502.29772)	(0.00064)	(0.00023)
	UMI	13067.144	0.01106	2.62301	21.12028	43062.05227	0.00013	0.00018
		(2695.07456)	(0.01651)	(0.38204)	(4.22181)	(2695.07456)	(9e-05)	(0.00012)
2	**HI**	37419.90094	0.02788	3.14433	23.49711	26451.18389	0.00089	0.00052
		(12784.42593)	(0.04071)	(0.34418)	(3.90823)	(12784.42593)	(7e-04)	(0.00023)
	UMI	15918.4969	0.01196	2.74514	22.43047	47952.58793	0.00017	2e-04
		(2212.68698)	(0.0171)	(0.39226)	(2.48808)	(2212.68698)	(0.00014)	(0.00013)
3	**HI**	40502.89281	0.02791	3.22801	23.19879	33846.24532	0.00095	0.00056
		(12795.55901)	(0.03897)	(0.33779)	(2.92552)	(11497.45904)	(0.00072)	(0.00023)
	UMI	19313.42204	0.01189	2.83103	25.73542	53978.02092	0.00019	0.00023
		(2796.21184)	(0.01579)	(0.36881)	(3.44903)	(2796.21184)	(2e-04)	(0.00016)
4	**HI**	41034.98161	0.0276	3.30779	20.94345	44805.87912	0.00098	0.00057
		(13604.60253)	(0.0389)	(0.3286)	(3.74267)	(11243.97789)	(0.00074)	(0.00022)
	UMI	21663.69316	0.01299	2.89713	25.29605	62776.98385	0.00017	0.00022
		(3525.76803)	(0.01658)	(0.33648)	(4.89457)	(3525.76803)	(0.00014)	(0.00015)
5	**HI**	44426.14846	0.02747	3.39395	21.61699	50431.78703	0.001	0.00053
		(15201.46561)	(0.03881)	(0.33706)	(3.84757)	(12516.3044)	(0.00076)	(0.00023)
	UMI	24217.20521	0.01344	2.96387	24.97617	69064.73694	0.00027	0.00023
		(4069.27638)	(0.01735)	(0.30389)	(5.98244)	(4069.27638)	(0.00024)	(0.00017)

Note: Standard deviations in parentheses; Classification: 2022 World Bank Classification by income.

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