Revisiting the Economic Growth Literature: Are the Effects of Innovation on Growth Consistent with Time and Differing Economic Development Stages

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Abstract

This research contributes to the economic growth literature by revisiting old literature with up-to-date information. While previous literature sought to highlight the importance of innovation concerning economic growth, this paper adds an interaction with time and economic development stage, with the research question: **How does the effect of innovation on economic growth change with time and economic development stage**? This study draws on impressive data collection by the OECD and the World Bank permitting the use of panel data on 39 OECD countries for a time period of 31 years.

This study uses three proxies for innovation; Research and Development Spending per Capita, Patenting per Capita and Researchers per 1000 employed. The findings indicate that the time interaction between innovation and economic growth is sensitive to the proxy use of innovation and variable specification. Moreover, the study shows that a lower economic stage is associated with a greater economic growth as a result from innovation, but this is also dependent on which proxy is used for innovation.

Contents

Introduction 4
Literature review 7
Economic growth literature 7
Measuring innovation 9
Research and development as an innovation indicator. 9
Patenting as an innovation indicator. 11
Mechanisms of innovation 12
The Saturation of Innovations. 12
Diminishing Returns 14
Describing the data 19
Data 19
Variables 21
Panel settings: 21
Dependent variable: 21
Independent Variables: 21
Control variables: 24
Methodology 30
Correlation 30
Checking for stationarity 31
Normality 35
Results 40
Hypothesis testing 40
Robustness 51
Conclusions & Discussion 59
Limitations & Suggestions for further research 61
Implications 64
Appendix A 70

Introduction

While there is no absolute consensus among researchers, the economic growth literature is extensive, and generally agrees that population growth, capital accumulation, and technological progress are the crucial factors for economic growth. One such paper is *"A Model of Growth Through Creative Destruction"* by Aghion and Howitt (1992) which highlights that innovation is the driving force of technological and economic growth, since they find that growth results from technological progress, spurred by competition between innovators. Innovation is therefore the key to being competitive, which is more important than ever in today's global economy (Cantwell,2006). Failing to innovate means falling behind competitors and the threat of being replaced by better innovators, this is termed creative destruction, and is the essence of competition,

Innovation has been a driving factor for economic growth throughout history. The development of new technologies such as the steam engine, or the internet, has repeatedly led to significant productivity increases (Daemmrich,2017). Innovation comes in many forms, there is product, service, and process innovation. Each with a potential to disrupt the way business models operate, optimize organizational structures, and even strategize their marketing. Furthermore, there are different types of innovation, those being radical or incremental. Radical innovation refers to groundbreaking new technological advancements, whereas incremental is a slow improvement upon existing products.

One of the ways in which one can boost innovation is through investing in Research and Development (R&D). R&D activities enable firms to innovate (Mairesse & Mohnen, 2004) the aforementioned product, service of processes within a firm. This can lead to an increase in productivity, competitiveness, or efficiency, allowing for higher growth through either reducing costs or increasing revenue. Additionally, R&D has additional spillover effects that other firms may reap the benefits from, further promoting innovation, so much so that Audretsch & Belitski (2020) state that knowledge spillovers are more important than R&D for firm productivity.

Considering the complexity and ubiquity of innovation, it makes measuring it problematic. There is not one variable that can be used to accurately track innovation. Researchers often used proxies instead, most commonly investment in Research and Development or patenting data (Caballero and Jaffe,1993 and others). Romer (1986), for example, was one of the pioneers of using R&D and managed to endogenize a growth model through knowledge accumulation and contributed to the literature with the inception of the R&D models, which many subsequent researchers built upon, the use of R&D then became the staple form of measuring innovation in economic growth literature. However, as will be discussed further on, this carried some pitfalls. It can be summarized in short, however, by a lack of data availability, and the unwillingness of researchers to revisit this topic. While there are more recent papers on this topic, Ulku (2004), Hasan & Tucci (2008), Cameron (1996) influential among the more recent works. However, these may still be considered dated. The consensus from these papers is that there is a significant positive effect between investing in R&D and economic growth.

Some researchers, however, elected to choose patenting data to describe innovation Jalles (2010). Unfortunately, similarly to R&D data, this is imperfect. While patenting might signify the inception of an invention, it fails to assess how much benefit this invention might bring, moreover, not every invention is patented, and not every sector has the same propensity to patent (Mansfield,1986 and Moser,2013).

Furthermore, innovating can affect different countries differently in terms of growth. For example, an innovating country will reap benefits of innovation differently depending on their infrastructure, countries with better infrastructure and ability to harness innovation will see more growth benefits. This is discussed in the book 'Innovation and Entrepreneurship in Developing Countries' by Naude, Szirma & Goedhuys (2011). More specifically they describe the benefit of innovation to be dependent on the characteristics of the system of innovation within they are embedded.

While the benefits of innovation vary between countries, there also appears to be a variance with time. Researchers found that the effectiveness of R&D has decreased, alongside this, the size of patenting (in terms of average number of ideas in patenting) has been declining since

1970. According to Caballero and Jaffe (1993), a patent in 1990 contained 10% less ideas than patents in 1970. Aghion & Howitt (1968) state that this is due to the perpetual increase in technological complexity, resulting in a continuous increase R&D to maintain a constant rate of innovation. Moreover, as the economy grows, new innovations will be affecting a smaller portion of the economy, and innovations are more likely to be niche and specific, this means that the benefits of these innovations do not see as many spillover benefits, and thus the impact as a whole is smaller. The existing literature as such suggests that the impact of innovation on a country's economy will likely reduce as countries continue to grow over time. Furthermore, countries may also experience the relationship of innovation on economic growth differently depending on their unique characteristics and their ability to foster an innovation thriving environment.

The research question of this paper is therefore as follows: "**How does the effect of innovation on economic growth change with time and economic development stage**?"

Much of the literature is focused on how economic growth is driven, and the central role that innovation plays in that, some examples that have already been mentioned are by Aghion and Howitt (1992), Ulku (2004) and more. While establishing this relationship is essential for policymakers and macroeconomists to promote economic growth adequately, the question on whether or not this relationship holds up over time is not thoroughly researched, the majority of the works in this field are quite dated. While this may not necessarily be detrimental, since scholars, for the most part, concur on the topic. It does raise the question how well it holds up as time has passed. It is because of this that I intend to reexamine the existing literature, and add onto it by investigating how their findings have held up, and how time affects it. This is even more prevalent due to the increasing globalization, which is increasingly shaping the interconnectedness of economies worldwide and shifting the way in which economies function (Samimi & Jenatabadi,2014). The timing of this research is also relevant, since the start of the 21-st century has termed the fourth industrial revolution (McKinsey & Company, 2022).

This also ties into the importance of testing whether economic development stages influence the effect of innovation on economic growth. The Global Entrepreneurship Monitor puts forth three types of economic development phases which contain factors that the Global competitiveness Report and the Global Innovation Index also discuss. For example, the most developed economies (Innovation-driven), have access to the best labor and their governments seek to bolster innovation through policies, according to the Global Entrepreneurship Monitor. Economies may also find themselves in transition phases to achieving higher economic development. This naturally raises the question as to how these countries compare in terms of achieving growth as a result of innovation. Will the countries that are most developed and innovation focused see higher growth due to innovation? Or is it the less developed economies that experience a type of catch—up effect?

To answer these questions a combined dataset of the OECD statistics and the World Bank has been constructed, on which panel data regressions will be performed. However, first, sections of the vast economic growth literature will be reviewed. Afterwards, a thorough description of the dataset and variables will be discussed. Next, the methodology regarding the econometric models will be discussed, and finally, the results will be presented, interpreted and discussed.

Literature review

Economic growth literature

There has been a plethora of economic growth literature, many of such research focus on why countries vary in economic growth, how some catch up faster than others, and why some countries remain poor. However, researchers aren't always in concurrence with one another. There is for example, the discussion on whether growth can be attributed to predominantly exogenous factors, or endogenous. Early developments in the research generally favored exogenous growth models such as the Solow Growth model in *A Contribution to the Theory of Economic Growth* by Solow (1956). This model is still widely used to explain growth. At the core of this model is the assumption of constant rate of technological progress, which is exogenously determined and unaffected by the level of output or investment. However, researchers became discontent with this dependence on exogeneity as a core part of the model. It is therefore that Arrow (1962) in *'The Economic Implications of Learning by Doing'*, introduced an endogenous model, with as the precipice that the acquisition of knowledge is endogenous (termed "learning"). This learning is then put into action in order to facilitate innovation, productivity and fostering growth in the human capital development. As such it is an increase in knowledge that fosters technological, and consequently economic growth.

Having paved the way for endogenous models, Romer (1990), alongside Grossman and Helpman (1991) and Aghion and Howitt (1992) built on this concept. At the core of their work is the emphasis on technological innovation and knowledge accumulation. This opposed the neoclassical approach at the time, which focused on diminishing returns and capital accumulation. Alongside this, was the possibility of increased returns introduced in Romer(1986), further opposing exogenous growth theories. Increased returns meant that richer economies could spur even further ahead due to the endogeneity of technological progress and knowledge acquisition (learning). In other words, an increase in knowledge through learning can have a spillover effect on even more knowledge and innovation, and consequently growth. This inherently contradicted the diminishing returns and convergence theories, stating that smaller/poorer economies would catch up to large economies at one point. Consequently, theorizing that richer economies could stay steps ahead, and even grow disproportionately faster. This is an important distinction for this research, since depending on the type of economy, the expectation of growth rates varies greatly.

Further contributions to the endogenous growth literature can be credited to Romer, he developed a model that emphasizes the importance of ideas and knowledge through firms and competitive agents that seek to profit maximize by investing in R&D, this was presented in *Increasing Returns and Long-Run Growth* by Romer(1986), these were referred to as R&D growth models.

Other influential research in this time concurred with the importance of R&D with respect to growth, for example, in *'A Model of Growth through Creative Destruction'* by Aghion and Howitt (1992). In this research the focal point is creative destruction, a term coined by Schumpeter (1942). This concept entails to the way in which new innovations and technologies displace already existing technologies, allowing for improvements and economic growth in the long term. In their research, they conclude that growth is a result exclusively from technological progress, resulting from innovation between competing firms. These innovations can in turn be used to produce at a more efficient rate. Firms will be motivated to pursue these innovations so long they can capture the monopolistic rents associated with these innovations.

The importance of technological progress and innovation is evidently a common theme when it comes to explaining economic growth. Innovation is described as a continuous process that seeks to replace itself to improve and is necessary for permanent sustained growth Aghion and Howitt (1992). Other researchers such as Ulku (2004) attributes innovation to investment in research and development (from here on R&D) using human capital and existing stock of knowledge. These factors, together, lead to a permanent increase in the total output, and thus, gross domestic product growth.

Measuring innovation

The issue that arises when investigating the relationship between innovation and economic growth is that innovation is a complex process that cannot be easily measured. However, as previously mentioned, researchers believe that R&D acts as a driving force towards innovation. Which is why it comes to no surprise that many scholars have elected to use R&D spending as a proxy for innovation (Ulku,2004, Hasan & Tucci,2008, Jalles,2009, Cameron,1996). This, however, is not the only proxy used, another popular choice is using patenting data, since this can be used to track the number of inventions that are created, which is synonymous with the amount of ideas or technology created. Some other proxies were also used by researchers such as Jalles (2009), who identifies that the best proxy for innovation is still up for debate, and proposes two new proxies: patents per 100,000 inhabitants and an intellectual property rights index. Lastly, some researchers also chose to incorporate the per capita number of researchers involved in innovation (Jones,1995). Considering the R&D and patenting are by far the most popular choices this research will use these innovation indicators. In the following section these indicators will be evaluated.

Research and development as an innovation indicator.

R&D costs are the most popular indicator for innovation in the literature, this is not unsurprising, since R&D is easily quantifiable, and well tracked. This, however, was not always the case. Cameron(1996), points out that older paper leaned towards R&D since R&D data was the easiest to compile. While this is not necessarily problematic, Griliches and Lichtenberg (1984) extensively speak about the limitations of R&D as a variable. They mention that the only good source of R&D data was found at the Census Bureau for the National Science Foundation, which raised two issues. Firstly, the R&D surveys are based on company reports, these companies were separated based on their main activity line. Problematically, most of these R&D firms are conglomerates that have a wide scope of production. Therefore, the reporting of R&D is subjective to the firm, as well as the sector that it pertains to. Secondly, a substantial number of firms perform R&D activities that are not directly related to the processes and products in their industry. For example, a conglomerate might elect to put their R&D in a country other than the headquarters for tax reasons, or even outsource their R&D expenditures. This can create variance in the reporting of innovative origins, end points and even further use cases, such as inventions stemming from this research.

Moreover, as Crosby (2000) importantly points out, R&D is merely an input to the level of innovation, this means that the relationship between R&D and the ambiguous variable of innovation are likely to be nonlinear, likely to vary with time, and likely to change depending on region and industry. This last notion is especially important to assess how innovation changes in different environments.

The benefit to using the R&D spending as an indicator of innovation is that it is the most well tracked data source. Bayarçelik, & Taşel(2012) also point out that investment in R&D is regarded as one of the best strategies to secure technological potential. Torun & Cicekci (2007) refer to R&D as creative work systematically undertaken to increase the stock of knowledge, and as previously mentioned, this enables innovation and in turn economic growth. To add on to this, Griffith, Redding & Van Reenen (2004) state that R&D has two roles, firstly, stimulating innovation, and secondly is imitating other discoveries. This means that countries that are behind in terms of knowledge, can still yield successful domestic innovation by pursuing R&D.

Therefore, while there are limitations to using R&D as a proxy for innovation, there is also a plethora of reasons why it is apt.

Patenting as an innovation indicator.

While many papers have highlighted the relationship between R&D spending and economic growth. The second most popular option elected was to use patenting data. Caballero and Jaffe as well as Mansfield (1985) used patenting data as a proxy for new ideas. The size of patenting (in terms of average number of ideas in patenting) was strongly increasing until the 1960-1970s. However, worryingly, has declined since then. According to Caballero and Jaffe (1993), a patent in 1990 contained 10% less ideas than patents in 1970. Mansfield(1986) and Moser(2013) also speak of the large variance in propensity to patent between sectors. This once again supports the notion that innovation is not at all linear, and different contexts will therefore yield different results.

An advantage of using patenting data is suggested by Crosby(2000) who accurately summarizes Schmookler(1966), who thoroughly analyzed the utilization of patent information, concluding that patents serve as supplementary data for significant inventions. Further suggesting that patent statistics are an accurate measure of the number of innovations created for the private sector across various domains and timeframes. There are also newer studies, by for example Nguyen & Doytch (2022) who prefer patenting data over R&D because they claim that innovation is better captured by patenting data since it is further along the chain of innovation (R&D is the initial stage, whereas a patent is intermediate). Maradana et al.,(2019) also favor patenting data, and use three types of per capita measures. They asses a presence of a relationship between innovation and economic growth that can be unidirectional and bidirectional, results vary from country to country and upon the indicator used.

The main criticism on patenting data is that the propensity to patent varies greatly depending on location and sectors as described by Mansfield (1986) and Moser(2013). Mansfield (1986) also points out that some sectors such as primary metals, instruments and motor vehicles do not make use of patenting at all. Which is why patenting data might not be as all-encompassing as R&D data. Subsequent research by Arundel & Kabla, (1998) revisit this, and find concurring conclusions, pharmaceuticals remain the most patenting industry. Other limitations are that not all innovations are patented, and that the value that a single patent brings to innovation is not assessable Breschi et al(2000).

Some authors have also established a relationship between the two innovation indicators mentioned. Caballero and Jaffe(1993), Jones(1995) Kortum(1997) found that the productivity of R&D has been declining over time, in other words, more R&D is required for new technology, and therefore the effectiveness of innovation, when using R&D as an indicator will weaken over time. Ulku (2003) adds on to this by summarizing '*Endogenous Growth Theory'* (1968) by Aghion & Howitt. They state that as technological complexity continues to increase, more and more R&D is required in order to maintain a constant rate of innovation. Moreover, new innovations end up affecting a smaller part of the total production in an economy, meaning that spillover effects are more limited. This phenomenon is sometimes referred to as oversaturation and will be discussed at length.

Mechanisms of innovation.

The Saturation of Innovations.

In Baumol (2002) a mechanism is introduced that further explores how the effectiveness of innovation on economic growth is reduced over time. This is referred to as the cost disease model and entails to the problematic saturation of innovation. The main argument is that over time, it becomes increasingly difficult for innovators to create radical innovations that disrupt the market. This is propelled by the term Asymptotic stagnation, which is a term coined by Baumol. In its essence is the idea that many sectors of the economy have as a characteristic a low productivity growth rate due to high labor intense activities, which are inherently difficult to automate and/or make more efficient through innovation. However, as the overall economy continues to grow, alongside wages, the productivity growth stagnates. Baumol uses as an example the sectors of television broadcasting and computer usage, when an innovation occurs, the output costs fall rapidly. However, eventually, it becomes more expensive as the costs of the inputs (labor and capital) continue to rise. This is because the cost of the input that is improving, and making the output cheaper, becomes a smaller share of that total cost. Meaning that the activity becomes increasingly expensive. This is especially true because there is not much room for more innovation due to the absence of ‘low hanging fruit’, as such any innovation will not improve the productivity at the same rate as the increase in costs. Inventions such as Henry Ford’s assembly line are an example of disruptive innovation that could be considered ‘low hanging fruit’. Since the innovation is relatively simple, with great productivity benefits. Nowadays, the market is too saturated and these ‘low hanging fruits’ are no longer available. This mechanism can be referred to as the saturation of innovation, and can be summarized by the increased difficulty of making truly revolutionary innovations, and consequently the increased difficulty in innovating due to rising costs.

Mokyr (2016) highlights the importance of the inevitable limitation of technological creativity and draws attention to the importance of technological revolutions. For example, they mention how in the 1700s China and European countries were equally developed, but they lack an industrial revolution meant that Europe could spur ahead. These events, however, are rare, especially since innovating becomes more and more difficult, as previously mentioned. Lastly, Kline & Rosenberg (2010) summarize innovation and further emphasize that in the 2000s innovation has changed. Before this time, being an innovator meant possessing a competitive advantage, however, now, it is seen as a cost to remain competitive. In some industries this is even more problematic since innovating might be extremely expensive. This creates further resistance to radical innovations and ties in with the theories presented by Baumol and Mokyr. This mechanism therefore acts as a limitation to Economic growth as a result of innovation, and is likely to continue to do so as time passes.

Caballero and Jaffe (1993) researched this and estimate equations to gauge a magnitude for creative destruction in different sectors. They find that creative destruction is on average present at a rate of roughly 4% per year, this means that on average, a firm that does not invent has their value decrease by about 4%. The drugs and pharmaceutical markets, however, see creative destruction up to 25%.

To reiterate, the saturation of innovations has led to a situation in which innovation is now a necessity, while simultaneously leading to less radical innovative opportunities. Because of this, innovation is less likely to create large ripples in the economy.

Diminishing Returns

Having explored the issue of innovation saturation, the issue of diminishing marginal returns to innovation will now be discussed. Aghion et al (2005) delve into detail how innovation affects competition. In their analysis, they find that "competition may increase profit from innovating", however, they find strong evidence that this relationship is U-shaped. Where laggard firms are discouraged from innovating at the very bottom, very competitive industries are incentivized to innovate, up to a point where the costs of innovations begin to outweigh the benefits.

Jones (1995) had previously touched on this point and states that in many countries a tremendous rise of R&D investment has been recorded, however, the same cannot be said for their growth rates. In his paper he calls the rejection of scale effects controversial. When this is tied together with the work of Aghion et al (2005), who find that innovating is diminishing in utility when competition increases, and Aghion & Howitt (1968), in which is stated that the continuous increase in technological complexity, more and more R&D is required to maintain constant innovation. The idea that innovation fosters growth, but experiences diminishing returns becomes enticing. The notion that laggard firms are discouraged to innovate due to low innovation (as proposed by Aghion et al, 2005) reinforces this idea, since it is the laggard firms that can reap the most benefits from innovating, if they are slow to adopt new technology, the value of new innovations may decline as time passes, since early adopters will use the competitive advantage to foster growth. However, as more companies adopt the innovation, the benefits will be spread between these companies, leaving laggard firms with innovations that are less valuable than in its inception. This results in lower marginal benefits, hampering economic growth.

Considering the mechanism of over saturation of innovation and the diminishing returns I hypothesize that:

H1: The effect of innovation on economic growth diminishes over time.

The literature is overwhelmingly supportive of the notion that the effectiveness of innovation, measured through the indicators previously mentioned, have become less effective as time has passed. This is especially true in the case of this paper, where a majority of the countries are extremely well developed, and rank highly on the competition index.

While the effect of innovation on economic growth might be changing over time, this is not the only factor that might impact it. As previously mentioned, and highlighted, the ability for innovation to thrive depends on the circumstances it finds itself in. This is where the Global Competitiveness Report by the World Economic Forum, as well as the Global Entrepreneurship Monitor will attend. These entities provide information and rankings on not only the factors surrounding economic growth available to all countries, but also attach so called 'pillars', which are the main ingredients for economies to thrive (Bosma & Levie, 2009). Some of these pillars include higher education and training, and business sophistication. Based on evaluating these pillars, countries are categorized into one of three economic development stages, which will be used in this report, they are: factor-driven, efficiency-driven or innovation-driven.

This specific categorization of countries is commonly used in these reports. In the Global Entrepreneurship Monitor, a description is provided[1]: The countries in this report are grouped into three stages of economic development as defined by the World Economic Forum's Global Competitiveness Report: factor-driven, efficiency-driven, and innovation-driven. This classification in phases of economic development is based on the level of GDP per capita and the extent to which countries are factor-driven in terms of the shares of exports of primary goods in total exports. Factor-driven economies are primarily extractive in nature, while efficiency-driven economies exhibit scale-intensity as a major driver of development. At the innovation-driven stage of development, economies are characterized by their production of

[1] https://www.gemconsortium.org/report

new and unique goods and services that are created via sophisticated, and often pioneering, methods. As countries develop economically, they tend to shift from one phase to the next.

The following definitions come from The Global Entrepreneurship Monitor directly. Followed by supporting information from the GEM conceptual Framework (used in GEM surveys).

1: Factor-driven economies: these are the least developed countries focused on agriculture and extraction businesses, with a reliance on natural resources.

Factor driven economies are the least developed type of economic stage, the requirements for a factor-driven-economy are basic institutions, infrastructure, macroeconomic stability and primary education.

2: Efficiency-driven economies, these economies have become more competitive, indulging in both process innovation and product innovation.

The efficiency-driven economies have higher education and training, goods and labor market efficiency, sophistication within the financial market, technological readiness, and a higher market size.

3: Innovation-driven economies, these are the most developed, business is extremely knowledge intensive, and as such innovation is required and crucial to success.

Lastly, the innovation-driven economies will have further business sophistication, higher innovation, physical infrastructure for entrepreneurship, improved R&D transfers, and government policy in support of Entrepreneurship.

The ranking of the countries based on the pillars is important because the ability for countries to harness the benefits from innovation will depend greatly on a few factors. Firstly, for innovation to thrive countries must be able to have enough investment available to them, in the previous section it was discussed how in order to stay competitive, innovation must be pursued. One of the Global Innovation Index’s main takeaways is that investment in innovation, but also infrastructure and education must be pursued for sustained growth, and that it is countries such as Switzerland, with high investment in these, that continue to rank highly in innovation performance. Investment in infrastructure and education is important because it allows the innovators benefits to be realized, without skilled labor and proper circumstances for innovations to thrive, growth might not be realized.

Alongside this is the importance of intellectual property protection, the Global Competitiveness index considers this while ranking these countries, intellectual property rights will assist innovators by allowing them to reap the fruits of their labour, but also, attract foreign investment. (Seyoum, B,1996)

Lastly, some countries will have more access to skilled labour than others, the Global Talent Competitiveness index reports the ability for countries to attract and retain skilled labor, and once again Switzerland and other innovation driven countries are at the top of the list. Skilled laborers are at the forefront of innovation and productivity, and as such will allow for greater growth rates.

The classification of countries by the global competitiveness index, as well as the Global Entrepreneurship monitor are a culmination of all these factors that will allow countries to grow from innovation, and it is those innovation-driven economies that are more likely to grow from innovation than the other two. Innovation-driven economies, as described, enjoy improved business sophistication, increased innovation, more skilled labor and improved establishments to promote and harness innovation.

Having acknowledged this, it must be evaluated whether the benefits of improved infrastructure for innovation will allow for higher growth, or if the saturation of innovations and the diminishing returns will mean that innovation-driven economies will in fact suffer growth losses.

Some of the attributes relating to innovation-driven economies and their impact on economic growth will be listed (based on the Global Competitiveness report and the Global Entrepreneurship Monitor)

1. Innovation-driven countries have access to the highest skilled workforce and research facilities. A skilled labor force can speed up economic growth (Kauhanen, 2020). This

aligns with the knowledge accumulation aspect of endogenous growth models, as a main driver of growth.

2. Innovation-driven countries are more innovation oriented; higher innovation levels can lead to an increase in productivity through channels previously discussed. Whether it be through new technologies, optimizing production or making business processes more streamlined. Moreover, innovation can have spillovers into other sectors, resulting in a boost to all affected industries.
3. Innovation-driven Government policies, Countries in innovation-driven countries have governments pursuing policies to bolster innovation, and harness the results from innovation through improved infrastructure, policies, and other factors. Allowing for higher rewards from innovation.
4. Highly developed countries act as hub for innovation, and therefore, investment. This investment can further exacerbate growth through increased innovation, but also by receiving new technologies, Li, & Liu(2005). Out of the world's 10 highest receivers of foreign direct investment, eight of them are innovation-driven economies, the other two being China and Hong-Kong, of which only China is efficiency-driven (Sánchez-Muñoz et al., 2021).

Considering these factors, innovation-driven economies seem to be the ideal economies for fostering innovation, and in turn economic growth. While these innovative countries might be running into issues regarding oversaturation of innovations, and diminishing returns to their investments, I believe that the factors discussed prior create an environment that is ideal for innovation and its benefits to thrive, and therefore hypothesize that:

H2: The effect of innovation on economic growth will be stronger for innovation- driven economies than efficiency-driven economies.

Describing the data

Data

The first dataset used in this paper are provided by the OECD statistics[2]. The OECD statistics provide datasets of patents by regions[3], as well as spending on innovation, and economic growth. The patent database contains patents from both the European patent office and the patent cooperation treaty. This data is collected with the goal to inform and steer economic social and environmental policies (OECD,2023), and will be used for the variable of interest as well as the main independent variables.

Secondly, the World Bank world development indicator databank[4] was used to obtain country specific data such as school enrollment and other. This dataset is the primary World Bank collection of development indicators, which is compiled from officially recognized international sources. Indicating that the data is both valid and reputable. The World Bank's mission is to reduce poverty, and believes statistics are a key to working towards that goal (World Bank,2023). Both the OECD and the World Bank cover a wide range of data collection topics, such as surveys, but also by cooperating with national statistics offices or other government agencies. Moreover, OECD members are required to report statistical information to the OECD.

The data used in this research is on 39 countries which can been seen on Table 1. Most of which are in the OECD, however, also some outside such as China. The entire dataset is comprised of 916 observations, however, each observation has numerous variables attached to it. Each observation represents a country within a specific year, with the years ranging from 1981 to 2012. The OECD data however, it is naturally not entirely complete, as countries joined at different times. Describing the time series data shows that the dataset is not perfectly

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[2] https://data.oecd.org/innovation-and-technology.htm#profile-Research%20and%20development%20(R&D)
[3] OECD (2023), "Patents by regions", *OECD Patent Statistics* (database), https://doi.org/10.1787/data-00509-en (accessed on 22 April 2023).
[4] https://databank.worldbank.org/source/world-development-indicators

balanced, and attrition is present in the data, out of the 32 periods (1981 to 2012) more than 25% of the countries had observations in all periods, and more than half were present in 23 periods. The minimum number of years one country was recorded for was 6, which is Chile.

Unfortunately, as previously mentioned, there were missing observations in the dataset. This meant that a lot of work had to be done to make the dataset perform as intended. Firstly, some countries such as Chile and Luxembourg had a lot of observations dropped. To determine whether to drop observations from the dataset it was decided that if, for a given year, a country was missing information on three measures of innovation (R&D expenditure, Researchers per 1000 employed and total patenting) it would be dropped. This meant that a reasonable amount of observations had to be dropped. This was exacerbated by the fact that various other data sources had to be used.

As previously mentioned, development indicators came from the world development indicators from the World Bank. It was from this dataset that variables such as total government debt, net imports, gross domestic product values, total school enrollment, unemployment and other variables, however, this dataset was in a wide format as opposed to the long format of the OECD datasets. Therefore, a transposition was required in order to merge the datasets.

Similarly to the OECD dataset, however, there were a lot of gaps in the data. Especially for some countries that were perhaps less developed at the time of recording, in order to overcome this issue, data from EUROSTAT was used to fill in blanks, where necessary. However, where this was not the case, interpolation techniques were used to fill in the gaps. For single gaps in data the average of the preceding and following year were taken, whereas larger gaps were modelled and forecasted in order to follow a trend. The way in which trends were made were using the forecasting function in Microsoft Excel, for example, if the years 1981 and 1982 (the first two years of the sample) were missing, the years after would be used to forecast their values based on the trend, conversely, for example if the later years were missing, the years prior could be used to forecast a trend. Data where this was not possible was removed or kept blank, for example 10 years or more missing.

Variables

Panel settings:

Country Code: The panel variable to which the unique identifier country_id is linked, which all other variables are linked to, 39 unique country names: Australia, Austria, Belgium, Canada, Chile, China, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Republic of Korea, Latvia, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States, the modal frequency is 32, the maximum amount of years. Whereas the lowest amount of frequency is Chile at 6.

Year: The data in the dataset is yearly data, ranging from 1981 to 2012. Not every year is present in the dataset 39 times, however, since some countries have missing data for a year. The modal frequency for years is 36 meaning that 36 different countries had data available for these years, the least recorded year is 1982, for which only 15 countries have data. The data is slightly negatively skewed, since there is more data present for the more recent years of the dataset, as to be expected.

Dependent variable:

GDP per Capita Growth: The dependent variable used is GDP per capita growth, in order to maintain consistency per capita is preferred over total GDP, and more valuable to answer the research question. For GDP per capita growth, the mean is 2.35% with the highest number being 13.64% in a singular year, that being Denmark in 1989.

Independent Variables:

While other research on this topic has usually focused on using a single proxy for innovation, the advantage of visiting this research in the current day allows me to use multiple proxies for innovation. These are R&D spending per capita, total patents per capita and the amount of researchers per 1000 people employed.

Total Patents per Capita: entails the total patents issued by a country within a full year, these patents are according to the region of inventors residence. The reason why this was picked over the applicants residence, is because the literature suggested that often, conglomerates have their R&D located outside of their country of origin, to avoid having inaccuracies in the data, the inventor's country of residence is preferred. The patents included are patents applied to the European Patent Office(EPO), as well as the patent cooperation treaty (PCT). There was some missing data, however, after interpolating using the average of the next year and the prior year, the data was completed, there are no missing values.

There are decimals reported in the patent count, this is because the data is based on the International Patent Classification, which uses fractional counts, perhaps estimates or calculations were made that included decimals to improve precision.

The variable *patent* was transformed into *patent per capita* using country population data, which will be used for the main regressions. Using per capita data will be more interesting than aggregate data, this is because a country like the United States, an innovation hub with a large population has an incredibly high number of patents in comparison to other countries. Therefore, correcting for country size is necessary. This will allow for the comparison of innovation levels between countries on a more level playing field, enabling more accurate analysis of the true innovative capacity of the countries. For patent per capita, the mean was 122.40 (per million population), the highest number of patents per capita were 739.61, which was in Switzerland (2012). The lowest number of patents per capita were in Slovakia in 1990 & 1991, where zero patents per capita were reported.

R&D Spending per Capita: Similarly to patenting, there is total spending on R&D. This variable can be described as all R&D carried out by all companies, research institutes, university, government, or any other facility involved in R&D that are resident to a country. This also includes R&D that is funded from abroad (example: foreign direct investment). However, similarly to the patenting, this does not include domestic funding to R&D performed outside of the domestic country. To keep the measurement consistent, the indicator is measured using USD with constant pricing using 2015 as base year.

Similarly to patenting data, R&D spending will be in per capita values, since as previously discussed, per capita values will allow for the investigation of a country's true innovative capabilities. The mean R&D spending per capita is 528.29, and the maximum is 1,838.32, which is once again Switzerland (2012). The lowest R&D spending per capita is 11.18 which was China in 1991.

Researcherper1000Employed: This variable shows the amount of researchers per 1000 employed individuals in a country. Researchers are described as professionals that engage in the creation, conceptualization or management of new knowledge, products, processes methods or systems. The mean is 5.35, meaning that on average out of all the countries, out of every thousand employed individuals 5.35 will be researchers. The highest number is 17.20 for any given year, in Finland. Because this is used as an indicator in some research (Jones,1995) it will be used as supplementary proxy for innovation in addition to R&D per capita spending and patenting per capita.

Binary variable for economy type: As discussed in the previous section, a country may be classified as either:

1: Factor-driven economies: these are the least developed countries focused on agriculture and extraction businesses, with a reliance on natural resources.

2: Efficiency-driven economies, these economies have become more competitive, indulging in both process innovation and product innovation.

3: Innovation-driven economies, these are the most developed, business is extremely knowledge intensive, and as such innovation is required and crucial to success.

The dataset used in this paper unfortunately does not contain any countries from factor-driven countries, there countries are predominantly African and less developed Asian countries of which not much data is available, therefore, a binary variable is created that take the value one for countries that are innovation-driven and a value of zero for countries that are efficiency-driven. The mean of this variable is 0.75, indicating that three quarters of the dataset is an innovation-driven economy. To determine whether a country is part of innovation driven economies or efficiency driven the Global Entrepreneurship Monitor 2012 Global report was used, in which a table, supported by reasoning is provided under which each country is assigned a category.[5]

It is possible for countries to move from one economic stage to the next. However, having investigated the GEM reports from 2008 onwards, the country Hungary has been classified as in transition to an innovation- economy since 2008. It is therefore safe to assume that the movement from one stage to another is a long-drawn-out process. As such, it is assumed that the country's economic stage is constant throughout the period of interest.

Control variables:

Urban population: The fraction of population that lives in an urban area. Since there is often a connection between urbanization, innovation and economic growth, this is due to a higher concentration of people and therefore availability of talented people and facilities for them to thrive (Henderson, 2000). Moreover, a closer spatial proximity will lead to better spillovers and efficiency in markets, also, there are often economic clusters around universities, this may therefore influence the innovation capabilities. On average, 72.7% of people in the data live in urban areas, however, this depends quite heavily on the country. China for example, has most of their people in rural areas, only 27.3% live in Urban areas. Whereas a Country like Belgium has the highest urban population for a given year, at 97.74%.

Net migration per capita: A country with a high positive net migration enjoys the benefits that migration brings, a high influx of people means that there is a lot of potential knowledge being added to the knowledge stock, Bove & Elia (2017) found significant effects that migration leads

[5] https://www.gemconsortium.org/report/gem-2012-global-report

to a growth in real GDP per capita, although this is more consistent for developing countries. Net migration per capita has a mean of 1,719.09. This, however, has very large variance, the standard deviation 4,094.88, Ireland in 2006 enjoyed the highest amount of net migration per capita at 22,442.14 people.

SecondarySchoolEnrollment: The amount of people attending secondary school, this is important because a higher rate of secondary school enrollment could lead to having a better educated population, increasing the pool of talented individuals. Barro (2013) finds that education to be an important determinant of economic growth. The mean for portion of enrollment into secondary school is 85.28%, the highest percentage of secondary school enrollment comes from Sweden in 2005 at 99.83%, whereas the lowest was South Africa in 1983 at 40.05%.

Trade: This variable acts as a proxy to gauge how open a country is. The specific variable used is net imports, which was calculated by subtracting net exports from imports, all as a portion of GDP. Ulku (2004) and Hasan & Tucci (2008) are some examples of research that include a proxy for openness. Bahmani-Oskooee & Niroomand (1999), find significant results between economic growth openness. On the other hand, Yanikkaya (2003), find a positive relationship between trade barriers and economic growth. The mean value for net imports was -0.86%, while the maximum was 20.64% which was Latvia in 2006. The minimum value was -32.32% in Luxembourg in 2009.

Life expectancy: Including life expectancy may isolate the unique impact of innovation, it is entirely possible that life expectancy may impact both innovation and growth through later retiring ages and more potential for innovation for example, conversely, rising life expectancies might lead to aging populations, which could hinder economic growth, as such controlling for such a confounder may assist in isolating the effect of innovation. Kunze (2014) finds evidence for this, and discovers that Inverted U-Shaped relationship exists, where economic growth increases up to a point, and thereafter decreases, this is true for countries where bequests are absent. Otherwise, there is simply a linear relationship where rising life expectancy leads to decreased economic growth. The maximum value was 83.10 in Japan in 2012, the minimum value was 53.98, in 2005. The mean value was 75.94.

Unemployment: Total unemployment as a % of total labor force. The fact that unemployment can slow down an economy and therefore reduce economic growth is well known. In the dataset, the mean unemployment level is 8%, with the lowest unemployment level being 0.2%, this is Switzerland in 1983. The highest is 32.21% which is South Africa in 2003.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP Growth %	876	2.75	3.56	-14.63	14.23
GDP per Capita Growth %	916	2.35	3.61	-14.61	13.64
R&D Spending per Capita	914	528.29	414.80	11.18	1,838.32
Patents per Cap	916	122.42	147.53	0	739.61
Researchersper1000employeed	916	5.48	3.09	.067	17.21
Secondary school enrollment %	838	85.28	9.81	40.05	99.84
Unemployment	877	8.09	4.56	.2	32.31
Urban Population %	916	72.29	12.52	27.31	97.74
Net migration Per Capita	916	1,719.09	4,094.88	-15,048.62	22,442.14
Net imports(%GDP)	909	-.86	6.165	-32.32	20.64

To visualize the dataset the following tables are created: Table 2: Full Sample and Table 3: Sample ranked by Average Per Capita Values.

What is interesting here is that when looking at per capita values, we see a whole new list of countries, which are consistently ranking high amongst the different variables, as can be seen from Table 2. Luxembourg seems to be the highest innovator per capita from these metrics.

In the tables the averages are taken over the entire sample, from these tables there can already be speculations made about the correlation between R&D expenditure and patenting with GDP. We can see that richer, developed, economies dominate the entire list of innovation indicators. It is therefore likely that there is a positive correlation between countries output and its innovative indicators in average patenting and R&D spending. However, we can see that there is an outlier in China, in the list, their average GDP per capita growth is almost twice as high as the next country, while they are not prominent in innovation per capita measures. This once reinforces the need for per capita values since China's high population makes them a poor innovator relative to their population.

Table 2: Full sample

Australia	Luxembourg
Austria	Mexico
Belgium	Netherlands
Canada	New Zealand
Chile	Norway
China	Poland
Czech Republic	Portugal
Denmark	Romania
Estonia	Russia
Finland	Slovakia
France	Slovenia
Germany	South Africa
Greece	South Korea
Hungary	Spain
Iceland	Sweden
Ireland	Switzerland
Israel	Turkey
Italy	United Kingdom
Japan	United States
Latvia	

Table 3. Sample ranked by Average Per Capita Values

Rank	Average GDP per Capita Growth		Researchers per 1000 employed Averaged	Patent per cap. averaged		R&D per cap. averaged	
1	China	9.46	Finland 14.97	Switzerland	445.59	Luxembourg	1,614.95
2	Latvia	5.62	Sweden 8.87	Sweden	431.72	Switzerland	1,314.29
3	Korea, Rep.	4.93	Japan 8.47	Finland	342.59	Sweden	1,207.78
4	Estonia	4.48	Iceland 8.37	Germany	313.87	United States	1,128.00
5	Slovak Republic	3.93	Russian Federation 7.70	Luxembourg	291.84	Japan	949.02
6	Poland	3.40	Norway 7.70	Netherlands	259.22	Finland	942.87
7	Ireland	3.31	Denmark 7.15	Denmark	256.49	Germany	889.23
8	Turkiye	2.99	United States 6.91	Japan	214.94	Denmark	835.14
9	Canada	2.88	Korea, Rep. 6.82	Austria	200.77	Austria	751.28
10	Slovenia	2.78	Luxembourg 6.75	United States	173.47	Norway	740.79
11	Chile	2.62	Australia 6.75	Norway	158.51	France	740.57
12	Czechia	2.61	Canada 6.54	France	155.51	Netherlands	713.58
13	Romania	2.46	United Kingdom 6.45	Belgium	152.89	Iceland	688.59
14	Australia	2.23	France 6.45	United Kingdom	137.21	Belgium	661.43

Further observations that can be made from Table 2, are that there are a lot of "less developed" countries ranked highest in Average GDP per Capita Growth, these countries are also classified as efficiency-driven economies, which is categorized using the table in the appendix (From the GEM). That being said, it appears, from the table, that China's growth may be credited to other factors than innovation. As the table shows that China has almost double the Average GDP per Capita growth than the succeeding countries, but do not rank in the top 14 for any of the innovation metrics. While Luxembourg, Sweden, Switzerland and Finland rank highly for all the innovation metrics, they do not rank highly for GDP per Capita growth. This could indicate that these economies are suffering from the diminishing returns and over saturation mechanisms as discussed in chapter 1.

To further explore how the variables move relative to each other, line plots have been constructed to show how R&D per capita and patenting per capita move over the years, these are found in appendix A. A clear observation to be made is the apparent synchronization of the movement of patenting and R&D costs per capita. Nearly every country has curves that move similarly over time. This is in concurrence with the literature and the theories presented in Romer (1986) and Caballero and Jaffe (1993).

The observation to be made from the figures in appendix A is that the lower income countries show some more irregularities in the way the curves move, for example Chile, Slovakia and Estonia have more volatile curves.

Methodology

Correlation

Table 4: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Per Capita GDP Growth	1.000									
(2) Patents per Capita	-0.150*	1.000								
	(0.000)									
(3) R&D spending per Capita	-0.181*	0.879*	1.000							
	(0.000)	(0.000)								
(4) Researcher per 1000	-0.185*	0.715*	0.779*	1.000						
	(0.000)	(0.000)	(0.000)							
(5) Unemployment (%)	-0.048	-0.266*	-0.343*	-0.164*	1.000					
	(0.155)	(0.000)	(0.000)	(0.000)						
(6) Urban Population (%)	-0.228*	0.432*	0.522*	0.514*	-0.124*	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(7) Net Migration per Capita (%)	-0.146*	0.319*	0.449*	0.292*	-0.226*	0.281*	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(8) Net Imports (%GDP)	0.109*	-0.388*	-0.432*	-0.312*	0.126*	-0.238*	-0.350*	1.000		
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(9) Life Expectancy	-0.152*	0.542*	0.618*	0.528*	-0.334*	0.457*	0.358*	-0.184*	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(10) Secondary school enrollment	0.049	0.415*	0.457*	0.617*	-0.099*	0.402*	0.264*	-0.221*	0.599*	1.000
	(0.154)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	

**** p<0.01, ** p<0.05, * p<0.1*

In order to assess any potential issues concerning correlation between variables, a correlation table is constructed. The coefficient for this ranges from -1 to 1, -1 representing a perfect negative correlation and 1 representing a perfect positive correlation. If some variables are highly correlated with each other (otherwise known as multicollinearity), it could negatively affect the estimates that are calculated.

From the matrix there appear to be a few correlations present, this is decided by the rule of thumb that anything above the absolute value of 0.7 indicates a presence of multicollinearity, which is undesirable (Mukaka M. M. (2012)). It is observable that life expectancy is quite highly correlated with a lot of variables, while it does not pass this 0.7 threshold, it seems to be correlated with secondary school enrollment as well was unemployment, therefore, life expectancy will be omitted, since school enrollment is more likely to capture variation of the ability to harness the positive effects of innovation. Moreover, the independent variables are all highly correlated with each other, however, since they will not be present within the same models, this is not an issue, in fact, it can be considered a good thing since it is expected and desired that these variables capture the same type of variation (that of innovation). Without these variables, multicollinearity should no longer be a concern. Further than that, however, the correlation table can already indicate the sign of the estimated effect, since the indicators for innovation are all negatively correlated with per Capita GDP Growth, a negative relationship is expected.

Checking for stationarity

This research deals with panel data, which incorporates time series. It is critical that the data that is being used is stationary. Stationary data refers to the statistical properties remaining constant, stationary time series data have constant means and variances over time, allowing for statistical techniques to be applied accurately, in fact, it is often a prerequisite for many statistical models. In this specific setting, the data being stationary is important because if it is not stationary, it would suggest that there are underlying trends that might cloud the relationship with the variable of interest.

An example of non-stationarity is a unit root, which often happens in data with time, such as the one that I am using. A unit root refers to the value of the time series being correlated with their lagged value. The issue that arises from this is related to the accuracy of modelling, since unit roots can cause errors in the estimation, potentially altering the conclusions. It is therefore essential that we perform unit root tests. There are several methods to conduct these, however, since the data used in this research is unbalanced and has gaps, the Fisher type unit root test based on augmented Dickey-Fuller has been used to assess the stationarity of the most important variables.

Table 5: Dickey-Fuller Tests

Variable	panels	Chi2	pvalue
R&D per Capita	38	31.82	1.00
Patents per Capita	38	27.72	1.00
Researcher per 1000 Employed	38	70.98	0.58
Secondary school enrollment	35	111.64	0.00
Unemployment	38	49.60	0.99
Urban Population	38	156.28	0.00
Net imports	38	110.09	0.00
Net migration per Capita	38	216.09	0.00

The $H0$ $(null\ hypothesis)$ for such a test is that all panel contain unit roots, and the alternate Hypothesis $H1$ is that at least one panel is stationary. Observing the P-values of the variables, it is uncovered that R&D per capita, patenting per capita, researchers per 1000 employed, and unemployment all contain unit roots in every panel (P value>significance level of 5%). To ensure that the estimations will be accurate, data transformations will have to be used.

In order to make these variables stationary the first difference will be taken; this subtracts the variable value from the value of the previous observation. This removes underlying trends from data, and allows it to be stationary by ensuring that the statistical properties are constant. The downside to this, however, is that some information is lost, since the data now focuses on changes over time, which is not necessarily a bad thing in the context of this research. Verifying that the first difference helped reduce the non-stationarity of the variables can be seen in Table

6. From this table, it can be observed that the p-values are all 0, indicating that all relevant variables are now stationary.

The dependent variable in the dataset is GDP per capita growth, which by nature does not suffer from unit roots, since growth rates are relative to the previous period, and will therefore be the preferred dependent variable. This is also in line with the research question.

Table 6: Dickey-Fuller post First difference

Variable	Panels	Chi2	P-value
diff_GDP	38	400.938	0.000
diff_ R&D per Capita	38	321.494	0.000
diff_Researcher per 1000	38	653.922	0.000
diff_Unemployment	38	263.728	0.000
diff_Patent per Capita	38	537.069	0.000

The testing for the next property is heteroskedasticity, heteroskedasticity is important as one of the assumptions for panel data models. Heteroskedasticity pertains to the error term having equal variance across all levels of the independent variables. To test this, we first run a regression using the relevant variables on the independent variable GDP per Capita growth.

Table 7: Linear regression Model

	(1) GDP per Capita Growth
diff_R&D per Capita	0.00485 (1.33)
diff_Patent per Capita	-0.0000678 (-0.01)
diff_Researcher per 1000	0.183 (0.52)
diff_Unemployment	0.0463 (0.48)

Secondary School Enrollment (%)	0.0582***
	(3.35)
Net Migration (%)	-0.00000881
	(-0.27)
Urban population (%)	0.00439
	(0.34)
Net imports (%GDP)	-0.00724*
	(-2.22)
_cons	-2.489
	(-1.70)
N	755

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Afterwards, the Breusch-Pagan test for heteroskedasticity can be used, this test has a null hypothesis that constant variance is present, otherwise known as homoskedasticity. Since the P-value of this test exceeds 0.05, the null hypothesis is not rejected, indicating that the data does not suffer from heteroskedasticity. Heteroskedasticity is an important factor when it comes to the efficiency of the models, it means that the error term is correlated with the variable of interest.

H0: Constant variance

chi2(1) = 0.17

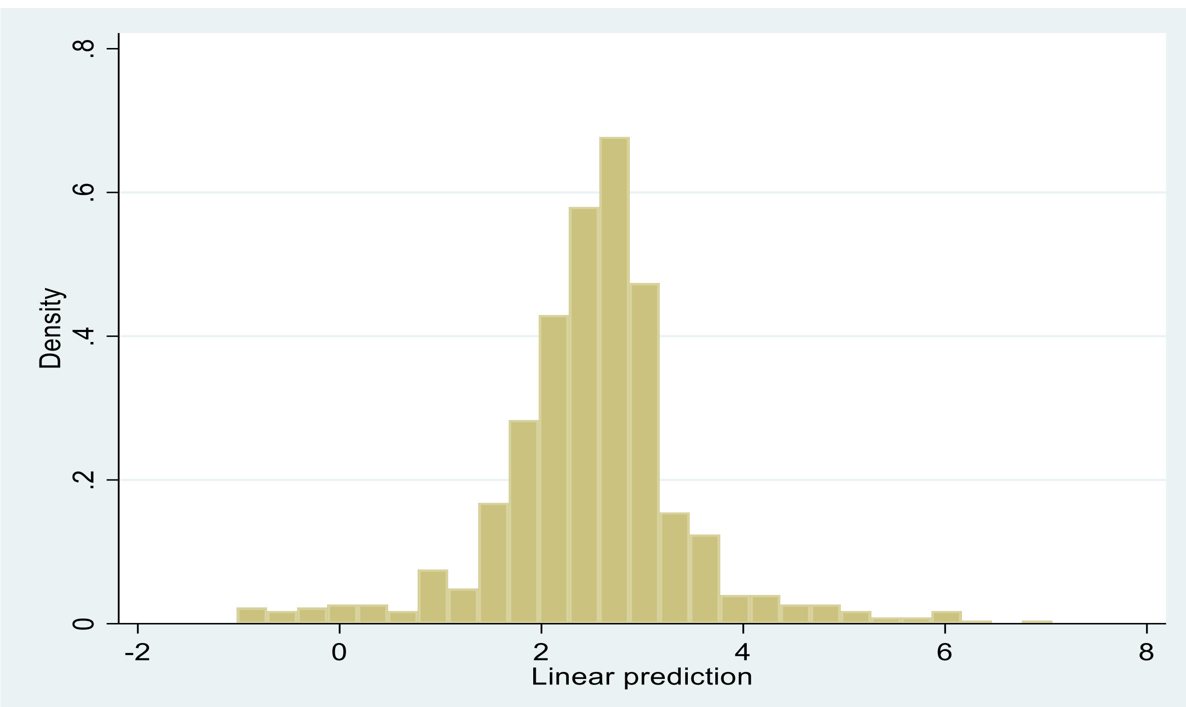
Prob > chi2 = 0.6799

Normality

In panel data the error term varies in both units and time, more specifically, unit heterogeneity and the idiosyncratic error. Within this dataset, the unit heterogeneity refers to the differences in the countries such as predisposition that are unobserved and therefore unmeasurable, some examples might include the innate innovative capabilities of the population. Whereas the unobserved time varying component might include capacity to work.

For our estimator to be unbiased, we must have that the error term is uncorrelated with the variable of interest (GDP growth). To learn more about the error term, the residuals the previous OLS regression were calculated by subtracting the predicted values from the observed values, representing the error term. Afterwards, they were plotted in this histogram. The histogram displays a bell-shaped curve, suggesting that the distribution of the error term is approximately symmetric and may be consistent with normal distribution. This is further supported by the fact that almost all the values are around the mean, with low frequencies in the tail ends.

Figure 1: Residual histogram



In panel data analysis such as this, the best regression method is a pooled OLS, however, the assumptions that must be satisfied for a pooled OLS to be unbiased are too strict. That being the absence of serial correlation, which in the case of this dataset is not possible. There are too many factors that affect economic growth, that are not in the model and error terms are therefore likely to be correlated with the time variable. Therefore, either a fixed effects or a random effects model will be used. The choice between a random effects model and a fixed model depends on the assumptions of the unobserved heterogeneity. The random effects model is preferred since it allows for measurements between observations as well as within variations, however, this will only hold if the assumption that the unobserved heterogeneity is uncorrelated with innovation holds.

Within the context of this research this would mean that the Exogeneity assumption, meaning that the error term (that being the individual fixed effect and the idiosyncratic shock) are uncorrelated with innovation. This is highly unlikely to hold, since innovation is an extremely complex metric, and it is near-impossible to be controlled for. Moreover, there are 39 countries in the dataset, some very different to others, it is therefore unlikely that the individual fixed effects are uncorrelated with innovation.

Because of this, it is likely that the Fixed effects model will be preferred in the context of the dataset, the Fixed effects model demeans the data to eliminate the unobserved heterogeneity.

Significant differences in time-varying coefficients would imply that the time-varying coefficients are crucial in assessing a relationship. If the coefficients are very different, it must mean that unobserved in the random effects matters, making Fixed Effects is more appropriate. The Hausman test tests this by comparing the estimates from the following Fixed Effects and Random Effects models. The $H0$ $(null\ hypothesis)$ is that the differences in estimates are nonsystematic. Therefore, if the P-value is smaller than 0.05(P<0.05) the null hypothesis is rejected, and the FE is preferred. The Hausman test will be performed for each of the different independent variable measures of innovation. From Table 8 (The 3 different Hausman tests), it is observed that all three tests have a P-Value of 0.00, since this is smaller than the significance level of 0.05, we reject the $H0$, meaning that the difference in coefficients is systematic, making it likely that the unobserved heterogeneity influences the GDP per capita growth.

Table 8: Hausman tests

Hausman with R&D	(1) GDP per Capita Growth (FE)	(2) GDP per Capita Growth (RE)
diff_R&D expenditure per Capita	0.00676^{**}	0.00704^{**}
	(2.88)	(3.08)
diff_Unemployment (%)	-1.203^{***}	-1.248^{***}
	(-19.49)	(-20.19)
Secondary School Enrollment (%)	-0.00695	0.00370
	(-0.32)	(0.26)
Net Migration per Capita (%)	-0.0000480	-0.0000592^{*}
	(-1.67)	(-2.35)
Urban Population (%)	-0.148^{**}	-0.0372^{**}
	(-3.18)	(-2.75)
Net imports (%GDP)	0.154^{***}	0.0781^{***}
	(5.19)	(3.93)
_cons	13.78^{***}	4.780^{***}
	(4.79)	(3.58)
N	755	755

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hausman (1978) specification test

	Coef.
Chi-square test value	38.572
P-value	0.000

Hausman with Patenting	(1)	(2)
	GDP per Capita Growth (FE)	GDP per Capita Growth (RE)
diff_Patents per capita	0.0132**	0.0124**
	(3.03)	(2.91)
diff_Unemployment (%)	-1.233***	-1.280***
	(-20.44)	(-21.10)
Secondary School Enrollment (%)	-0.0180	0.00182
	(-0.85)	(0.13)
Net Migration per Capita (%)	-0.0000368	-0.0000533*
	(-1.28)	(-2.12)
Urban Population (%)	-0.133**	-0.0355**
	(-2.86)	(-2.67)
Net imports (%GDP)	0.153***	0.0802***
	(5.18)	(4.07)
_cons	13.68***	4.871***
	(4.75)	(3.70)
N	759	759

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hausman (1978) specification test

	Coef.
Chi-square test value	44.923
P-value	0.000

Hausman with Researchers	(1)	(2)
	GDP per Capita Growth (FE)	GDP per Capita Growth (RE)
diff_Researchers per 1000	-0.308	-0.316
	(-1.39)	(-1.43)
diff_Unemployment (%)	-1.229***	-1.274***
	(-20.15)	(-20.76)
Secondary School Enrollment (%)	-0.00922	0.00645
	(-0.43)	(0.45)
Net Migration per Capita (%)	-0.0000477	-0.0000615*
	(-1.65)	(-2.42)
Urban Population (%)	-0.147**	-0.0339*
	(-3.16)	(-2.52)
Net imports (%GDP)	0.147***	0.0759***
	(4.98)	(3.82)
_cons	14.14***	4.527***
	(4.90)	(3.39)
N	759	759

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hausman (1978) specification test

	Coef.
Chi-square test value	44.92
P-value	0.000

Results

Hypothesis testing

In order to test the first hypothesis: ***H1: the effect of innovation on economic growth diminishes over time.***

A fixed effects model will be run, as discussed. However, a new variable will be created which is an interaction term between each of the innovation measures with the time variable year. The function of the interaction term is to see how the effect of innovation affects economic growth through another variable, in this case time. These will be run with every innovation proxy to make sure that the findings are consistent.

Table 9: Fixed Effect Model with R&D per Capita

R&D	(1) GDP per Capita Growth	(2) GDP per Capita Growth
diff_R&D per Capita Spending	0.00676**	0.618
	(2.88)	(1.21)
diff_Unemployment (%)	-1.203***	-1.203***
	(-19.49)	(-19.50)
Secondary School Enrollment (%)	-0.00695	-0.00345
	(-0.32)	(-0.16)
Net Migration per Capita (%)	-0.0000480	-0.0000433
	(-1.67)	(-1.50)
Urban Population (%)	-0.148**	-0.144**
	(-3.18)	(-3.11)
Net Imports (%GDP)	0.154***	0.148***
	(5.19)	(4.97)

Diff_R&D spending per Capita X Year		-0.000305
		(-1.20)
_cons	13.78***	13.21***
	(4.79)	(4.53)
N	755	755

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Fixed Effect Model with Patenting

	(1)	(2)
Patenting	GDP per Capita Growth	GDP per Capita Growth
diff_Patenting per Capita	0.0132**	1.489
	(3.03)	(1.02)
diff_Unemployment (%)	-1.233***	-1.235***
	(-20.44)	(-20.46)
Secondary School Enrollment (%)	-0.0180	-0.0178
	(-0.85)	(-0.84)
Net Migration per Capita (%)	-0.0000368	-0.0000334
	(-1.28)	(-1.16)
Urban Population (%)	-0.133**	-0.127**
	(-2.86)	(-2.72)
Net Imports (%GDP)	0.153***	0.150***
	(5.18)	(5.06)
Patent per Capita x Year		-0.000737
		(-1.02)
_cons	13.68***	13.23***
	(4.75)	(4.55)
N	759	759

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the first model, of which the regression output can be found in Table 9, the Fixed Effect model was run using R&D as the proxy for innovation, the coefficient prior to adding the interaction term is 0.00676, this is statistically significant at the 99% significance level (P<0.01). This means that a one unit increase in the first difference of R&D spending per capita is associated with a 0.68 percentage point increase in per capita economic growth, ceteris paribus. However, after adding the interaction term to the model R&D per Capita spending became insignificant. The interaction term has a negative sign, indicating that over time, the effect of innovation diminishes. However, this is also statistically insignificant(P>0.05), there is insufficient evidence to suggest that the interaction term has a significant impact on economic growth.

Per capita patenting saw similar motions as R&D per capita spending. In both instances (before and after adding an interaction), the proxy for innovation had a positive effect on Per capita GDP growth, while only after did it become insignificant.

The final model that was ran to test hypothesis 1 is using researchers per 1000 as a proxy for innovation. In this model, however, the effect of adding more researchers on economic growth was highly significant (P<0.001), however, only after the interaction term between this and time was introduced. The interaction term shows a negative sign, implying that as time passes, the effectiveness of adding a researcher per 1000 employed diminishes. Or the effectiveness of increasing innovation has a smaller effect on economic growth as time passes.

Table 13: Fixed Effects Model with Researchers per 1000 employed.

Researcher	(1) GDP per Capita Growth	(2) GDP per Capita Growth
diff_Researchers per 1000 employed	-0.308	217.3***
	(-1.39)	(3.77)
diff_Unemployment (%)	-1.229***	-1.244***

	(-20.15)	(-20.54)
Secondary School Enrollment (%)	-0.00922	-0.00141
	(-0.43)	(-0.07)
Net Migration per Capita (%)	-0.0000477	-0.0000423
	(-1.65)	(-1.47)
Urban Population (%)	-0.147**	-0.102*
	(-3.16)	(-2.16)
Net Imports (%GDP)	0.147***	0.128***
	(4.98)	(4.30)
Researchers per 1000 employed * year		-0.109***
		(-3.78)
_cons	14.14***	10.08**
	(4.90)	(3.30)
N	759	759

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

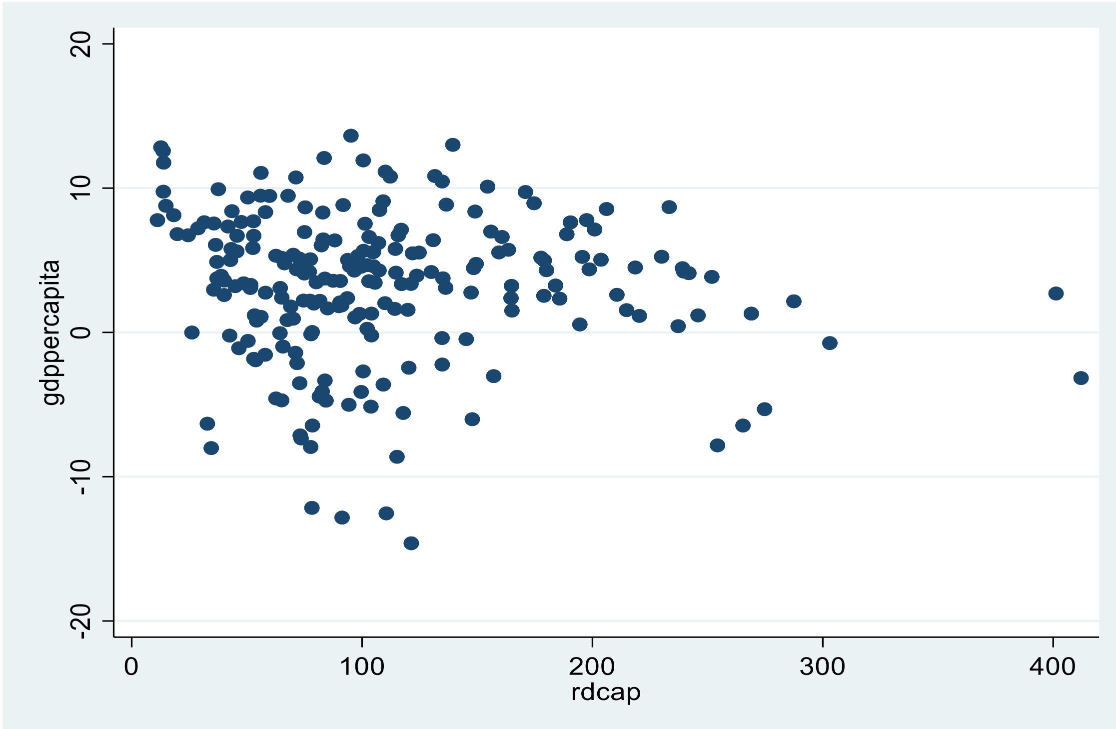
It is also noteworthy that in all of these models, unemployment, urban population and net imports are highly significant (P<0.01), all else equal, this means that these variables play an important role in the effect of innovation on economic growth.

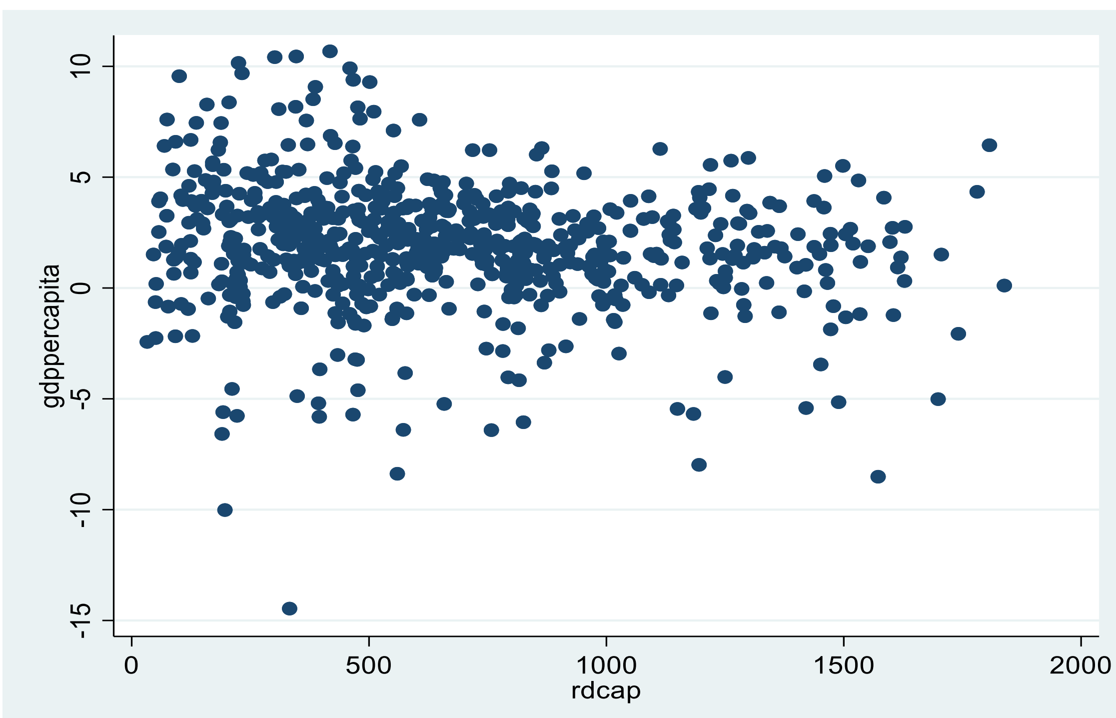
To test the second hypothesis:

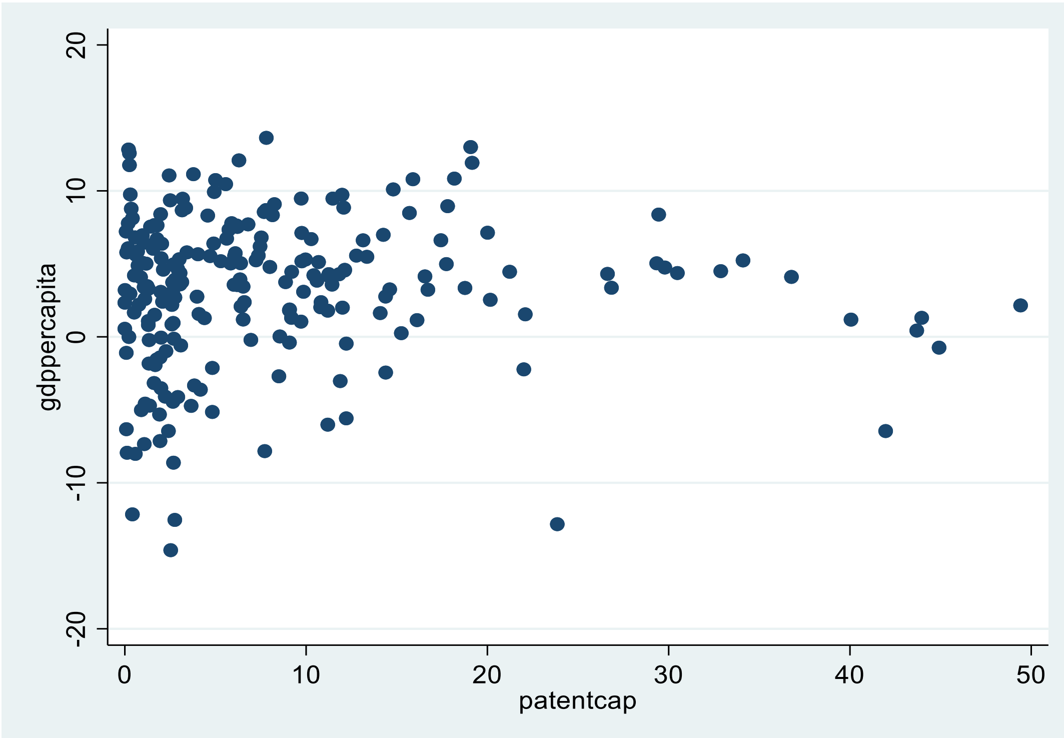
The effect of innovation on economic growth, will be the stronger for innovation- driven economies than efficiency-driven economies.

First, scatter plots are made of the variables of interest on economic growth for both economy types. From these there does not seem to be a positive relationship between the variables for either economy type with little difference between the two types of economies.

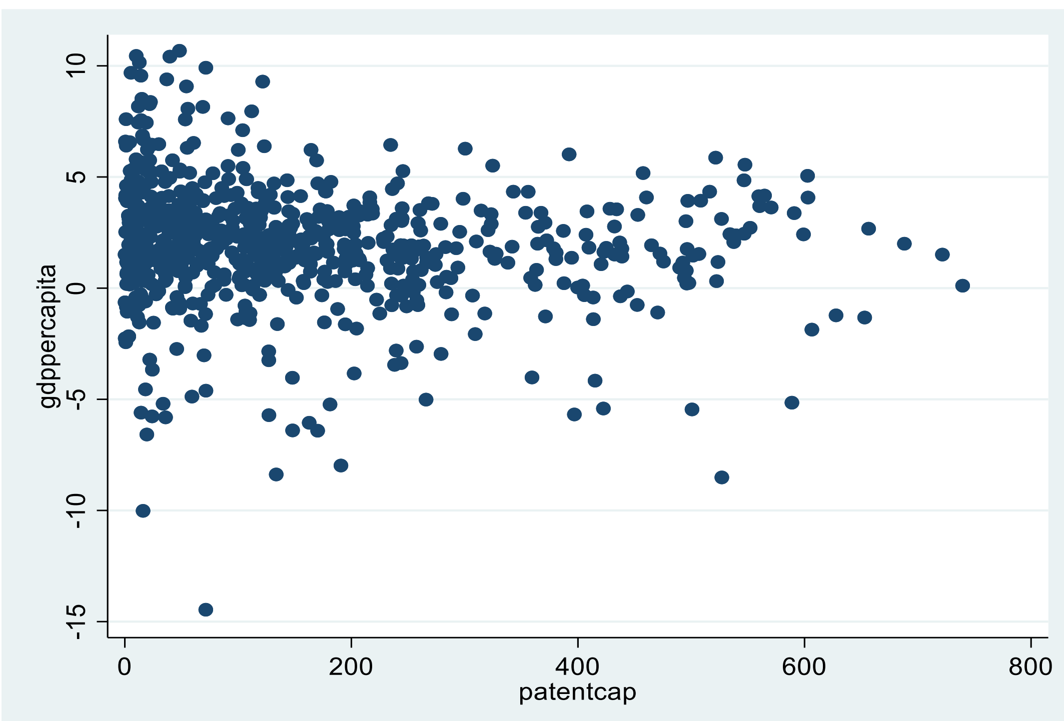
Figure 2: Series of scatter plots showing the different innovation measures against GDP growth for different country types (on top efficiency driven, and bottom innovation driven)


20
10
0
-10
-20
gdppercapita
0
100
200
300
400
rdcap

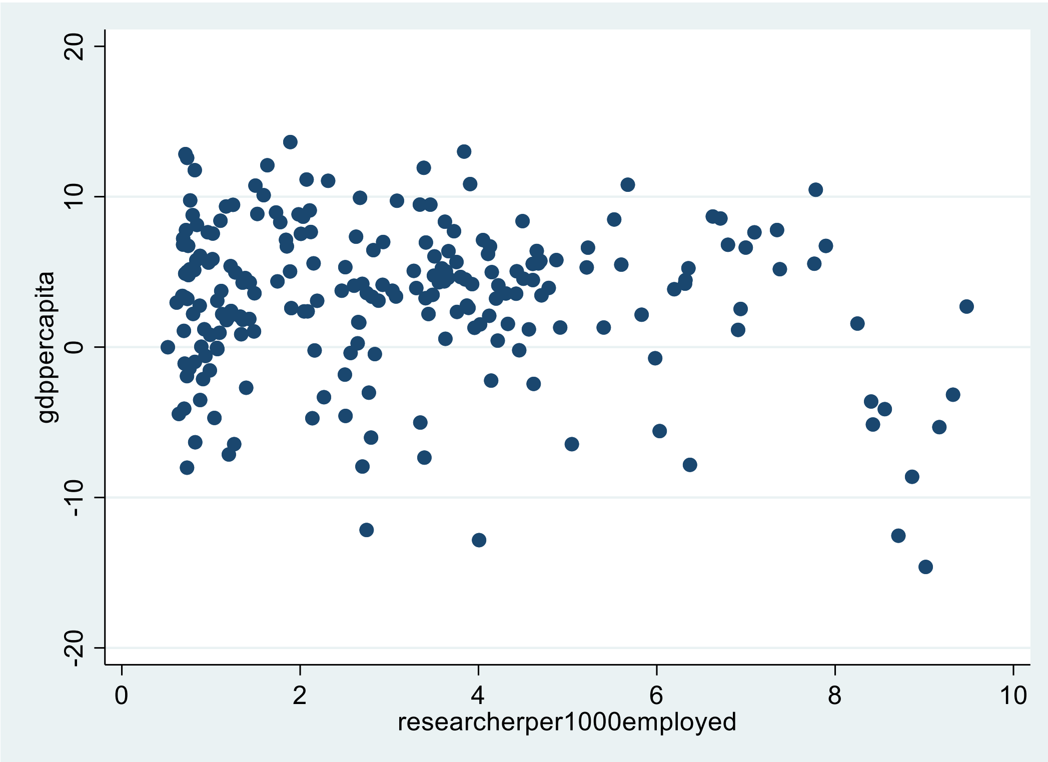

10
5
0
-5
-10
-15
gdppercapita
0
500
1000
1500
2000
rdcap

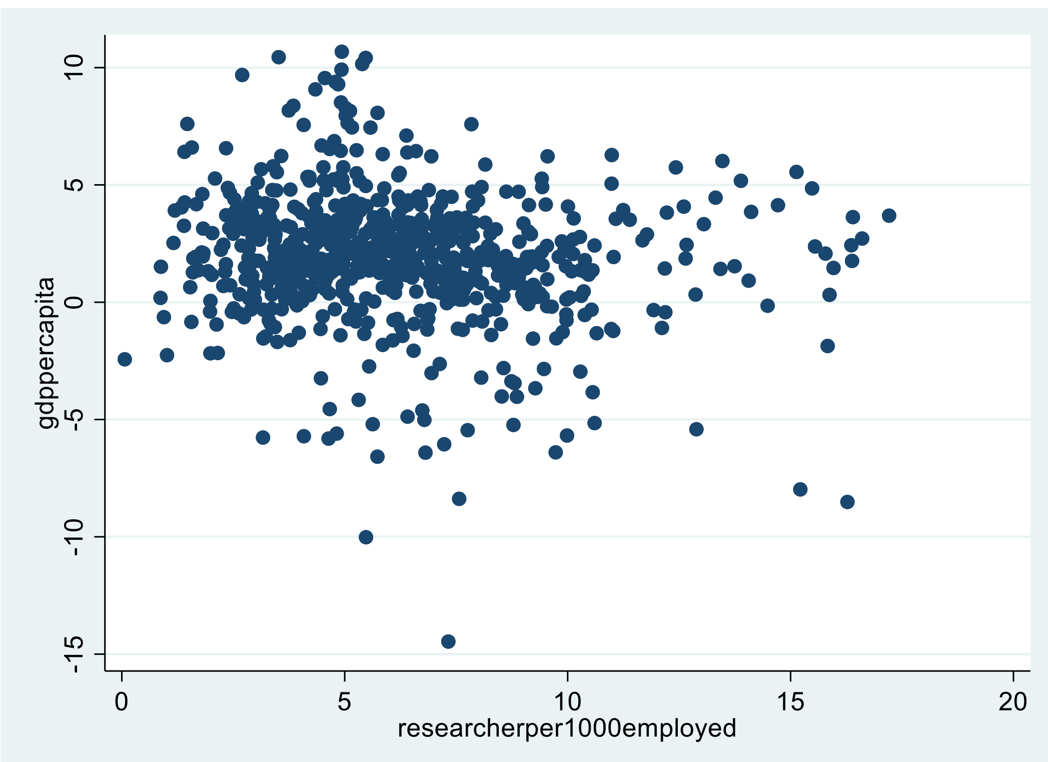


20
10
0
-10
-20
gdppercapita
0
10
20
30
40
50
patentcap



10
5
0
-5
-10
-15
gdppercapita
0
200
400
600
800
patentcap


gdppercapita
researcherper1000employed
-20
-10
0
10
20
0
2
4
6
8
10


gdppercapita
researcherper1000employed
-15
-10
-5
0
5
10
0
5
10
15
20

To test the second hypothesis: ***H2: The effect of innovation on economic growth will be stronger for innovation- driven economies than efficiency-driven economies.***

First scatter plots are made of the variables of interest on economic growth for both economy types. The scatters show that most of the values are randomly distributed around the zero GDP per capita growth. There is no real difference between the economy types from these graphs.

From these there does not seem to be a significant positive relationship between the variables for either economy type, and the difference between them also does not seem significant. This was already suggested by the many insignificant results found in the testing of hypothesis 1.

To test the hypothesis using a regression a fixed effects model is no longer feasible, the economy type is a time invariant characteristic, this makes it perfectly collinear with the individual fixed effects. Instead, a random effects model will be used, the random effects model will be ran, on its own, followed by the model including the binary variable that takes the value *one* if the country's economy is innovation-driven, or *zero* if the country is efficiency-driven. Lastly, an interaction term is created between the binary variable and the proxy of innovation. This model will be run three times for each of the proxy of innovation.

Table 14: Random Effects with Economy Type Binary & Interaction for R&D

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(3) GDP per Capita Growth
diff_R&D per Capita Growth	0.00704**	0.00718**	0.0487***
	(3.08)	(3.12)	(3.34)
diff_Unemployment (%)	-1.248***	-1.249***	-1.230***
	(-20.19)	(-20.12)	(-19.80)
Secondary School Enrollment (%)	0.00370	0.00777	0.00272
	(0.26)	(0.54)	(0.19)
Net Migration per Capita (%)	-0.0000592*	-0.0000601*	-0.0000574*

	(-2.35)	(-2.37)	(-2.27)
Urban Population (%)	-0.0372**	-0.0358**	-0.0357**
	(-2.75)	(-2.71)	(-2.67)
Net Imports (%GDP)	0.0781***	0.0735***	0.0742***
	(3.93)	(3.76)	(3.78)
Innovation-Driven Economy Binary		-0.160	0.0960
		(-0.42)	(0.24)
R&D per Capita * Innovation-driven Binary			-0.0424**
			(-2.89)
_cons	4.780***	4.444***	4.644***
	(3.58)	(3.38)	(3.51)
N	755	755	755

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the first regression, it is once again observed that R&D per capita has a positive statistically significant impact on GDP per capita growth. Afterwards, the binary variable was introduced, which has a negative coefficient, albeit of small magnitude, this means that innovation-driven economies experience less growth in general. However, this coefficient is not statistically significant (P>0.05), because of this, there is not enough statistical evidence to suggest that a different economy type will experience growth differently.

Afterwards, the interaction term between the innovation proxy (in this case R&D) and the innovation-driven binary is introduced. This interaction term is statistically significant (P<0.05) with a negative coefficient. Indicating that for R&D, innovation is converted to less economic growth for innovation-driven countries than efficiency-driven countries.

The same model will now be run using patents per capita.

Table 15: Random Effects with Economy Type Binary & Interaction for Patenting

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(1) GDP per Capita Growth
diff_Patenting per Capita	0.0124**	0.0123**	0.186*
	(2.91)	(2.88)	(2.23)
diff_Unemployment (%)	-1.280***	-1.281***	-1.275***
	(-21.10)	(-21.06)	(-21.02)
Secondary School Enrollment (%)	0.00182	0.00444	0.000603
	(0.13)	(0.31)	(0.04)
Net Migration per Capita (%)	-0.0000533*	-0.0000543*	-0.0000530*
	(-2.12)	(-2.13)	(-2.08)
Urban Population (%)	-0.0355**	-0.0348**	-0.0347**
	(-2.67)	(-2.63)	(-2.59)
Net Imports (%GDP)	0.0802***	0.0774***	0.0780***
	(4.07)	(3.95)	(3.96)
Innovation-Driven Economy Binary		-0.0788	0.0987
		(-0.21)	(0.25)
Patent per Capita * Innovation-driven Binary			-0.174*
			(-2.09)
_cons	4.871***	4.657***	4.814***
	(3.70)	(3.55)	(3.64)
N	759	759	755

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From this regression that includes the patenting per capita proxy, very similar results can be seen when compared to the R&D data, for the three regressions, countries that patent more see increased GDP per capita growth. Afterwards, the innovation-driven economy binary was added, this variable was statistically insignificant (P>0.05) for both models with-and-without the interaction term. Finally, after the interaction term was added, the independent variable patenting per capita shifted to a much higher magnitude, this might suggest that the association between innovation (using patenting as a proxy) varies quite significantly across the interacted variable. The interaction term itself is statistically significant(P<0.05), with a negative sign. Showing that efficiency-driven countries will benefit more from innovating in terms of growth than innovation-driven countries.

Lastly, the model is ran for researchers per 1000 employed.

Table 16: Random Effects with Economy Type Binary & Interaction for Researchers

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(3) GDP per Capita Growth
diff_Researchers per 1000	-0.316	-0.317	1.085
	(-1.43)	(-1.42)	(1.32)
diff_Unemployment (%)	-1.274***	-1.277***	-1.284***
	(-20.76)	(-20.73)	(-20.84)
Secondary School Enrollment (%)	0.00645	0.00908	0.00686
	(0.45)	(0.64)	(0.48)
Net Migration per Capita (%)	-0.0000615*	-0.0000649*	-0.0000658*
	(-2.42)	(-2.53)	(-2.56)
Urban Population (%)	-0.0339*	-0.0341**	-0.0336*
	(-2.52)	(-2.60)	(-2.52)
Net Imports	0.0759***	0.0726***	0.0750***

(%GDP)			
	(3.82)	(3.72)	(3.81)
Innovation-Driven Economy Binary		0.0462	0.218
		(0.12)	(0.56)
Researcher per 1000 * Innovation-driven Binary			-1.507
			(-1.78)
_cons	4.527^{***}	4.283^{**}	4.308^{**}
	(3.39)	(3.26)	(3.25)
N	759	759	759

For the final proxy of innovation, researchers per 1000 employed was used. Unlike the other two proxies of innovation, this model does not find any statistically significant results (P>0.05). For all three regressions, there is no statistically significant effect of innovating more (through means of increasing researchers concentration) on per capita GDP growth. Furthermore, there are no statistically significant results to suggest that innovation-driven countries see more economic growth than efficiency-driven countries. Lastly, there is not evidence to suggest that innovation-driven will see more growth as a result of increasing their researcher concentration.

Robustness

While the first difference variables may provide advantages through making the non-stationary variables stationary and assist in eliminating unobserved heterogeneity. This comes at a loss of information, the first year for each country was removed since there is no difference to be taken here. It is therefore of additional value to rerun the models using the original variables to see how the regressions behave. This is especially relevant for testing the first hypothesis, where the year effect is important.

Table 17: Fixed Effects Model Without First Difference (R&D per Capita)

	(1)	(2)
R&D per Capita	GDP per Capita Growth	GDP per Capita Growth
R&D per Capita	-0.00108	0.218**
	(-1.76)	(2.83)
Unemployment (%)	-0.136**	-0.132**
	(-2.94)	(-2.87)
Secondary School Enrollment (%)	0.0136	0.0147
	(0.54)	(0.59)
Net Migration per Capita (%)	-0.0000312	-0.0000325
	(-0.79)	(-0.82)
Urban Population (%)	-0.164**	-0.122*
	(-2.99)	(-2.17)
Net Imports (%GDP)	0.165***	0.164***
	(4.35)	(4.35)
R&D per Capita * Year		-0.000108**
		(-2.84)
_cons	14.92***	10.61**
	(4.30)	(2.81)
N	795	795

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From this table it is observable that when the interaction of time with R&D per capita spending is added, there is a very significant effect for both R&D per capita spending(P<0.01) and the interaction between R&D per capita spending and years (P<0.01). Albeit that the coefficients are both smaller than when the first difference variables were used. This effect is visible in all proxies of innovation. This supports evidence for hypothesis 1.

Table 18: Fixed Effects Model Without First Difference (Patenting per Capita)

Patenting per Capita	(1) GDP per Capita Growth	(2) GDP per Capita Growth
Patenting per Capita	0.00151	1.265***
	(1.07)	(4.83)
Unemployment (%)	-0.128**	-0.121**
	(-2.77)	(-2.64)
Secondary School Enrollment (%)	0.00254	-0.00730
	(0.10)	(-0.30)
Net Migration per Capita (%)	-0.0000503	-0.0000397
	(-1.28)	(-1.02)
Urban Population (%)	-0.209***	-0.186***
	(-3.69)	(-3.32)
Net Imports (%GDP)	0.193***	0.203***
	(5.06)	(5.38)
Patents per capita * Year		-0.000628***
		(-4.82)
_cons	18.37***	16.59***
	(5.08)	(4.63)
N	797	797

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Fixed Effects Model Without First Difference (Researchers per 1000 Employed)

	(1)	(2)
Researchers	GDP per Capita Growth	GDP per Capita Growth
Researchers Per 1000 Employed	-0.173^{*}	36.19^{***}
	(-2.48)	(4.15)
Unemployment (%)	-0.122^{**}	-0.157^{***}
	(-2.64)	(-3.39)
Secondary School Enrollment (%)	0.0205	0.0256
	(0.81)	(1.02)
Net Migration per Capita (%)	-0.0000302	-0.0000305
	(-0.77)	(-0.78)
Urban Population (%)	-0.140^{*}	-0.0935
	(-2.51)	(-1.66)
Net Imports (%GDP)	0.160^{***}	0.150^{***}
	(4.25)	(4.02)
Researchers per 1000 Employed * Year		-0.0180^{***}
		(-4.17)
_cons	12.87^{***}	7.429
	(3.52)	(1.93)
N	797	797

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As mentioned, Table 17, 18 and 19 show that all three proxies have significant results for both the effect of innovation on per capita growth, and the interaction terms alike. However, prior to adding the interaction term the R&D proxy and patenting per capita proxy were insignificant. The fact that it becomes significant after adding the interaction term could suggest that the relationship between innovation and GDP per capita growth depends very much on the year, and that the association is likely not stable over time. The coefficient for the interaction term is highly significant for all three proxies of innovation (P<0.05) indicating that a negative relationship is indeed found.

When this is done with the regressions of the second hypothesis testing, we observe Table 20, the first Table shows the regressions for R&D, Table 21 shows the regressions with patenting, and Table 22 researchers.

Table 20: Random Effects Model Without First Difference Innovation-Driven Binary and Interaction(R&D)

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(3) GDP per Capita Growth
R&D per Capita	-0.00116*	-0.00105*	-0.00155***
	(-2.57)	(-2.31)	(-3.44)
Unemployment (%)	-0.0888**	-0.0891**	-0.0700*
	(-2.85)	(-2.90)	(-2.37)
Secondary School Enrollment (%)	0.0240	0.0298	0.0362*
	(1.46)	(1.81)	(2.25)
Net Migration per Capita (%)	-0.0000324	-0.0000318	-0.0000237
	(-0.99)	(-0.97)	(-0.75)
Urban Population (%)	-0.0314*	-0.0287	-0.0256
	(-2.01)	(-1.90)	(-1.82)
Net Imports (%GDP)	0.0666**	0.0620*	0.0467*
	(2.64)	(2.51)	(1.97)
Innovation-Driven Binary		-0.452	-0.713

		(-1.03)	(-1.72)
R&D per Capita * Innovation-driven Binary			0.0164^{***}
			(5.70)
_cons	3.978^{*}	3.578^{*}	2.742
	(2.52)	(2.33)	(1.86)
N	795	795	771

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the non-first differenced model for R&D, a negative correlation is found between innovation spending and per capita GDP growth. Indicating that there is a negative relationship between innovation and economic growth, this remains statistically significant when adding the binary variable and the interaction term (P<0.05). The interaction term is positive in this case and statistically significant, indicating that being an innovation driven country does in fact lead to higher returns to innovation (when using R&D as proxy).

Table 21: Random Effects Model Without First Difference Innovation-Driven Binary and Interaction(Patent)

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(3) GDP per Capita Growth
Patenting per Capita	-0.00170	-0.00162	-0.00251^{*}
	(-1.61)	(-1.54)	(-2.39)
Unemployment (%)	-0.0749^{*}	-0.0798^{**}	-0.0718^{*}
	(-2.48)	(-2.66)	(-2.48)
Secondary School Enrollment (%)	0.0217	0.0291	0.0339^{*}
	(1.35)	(1.78)	(2.11)
Net Migration per Capita (%)	-0.0000488	-0.0000439	-0.0000347
	(-1.53)	(-1.37)	(-1.10)

Urban Population (%)	-0.0362*	-0.0318*	-0.0295*
	(-2.45)	(-2.18)	(-2.17)
Net Imports (%GDP)	0.0753**	0.0692**	0.0635**
	(3.13)	(2.90)	(2.75)
Innovation-Driven Binary		-0.636	-0.735
		(-1.52)	(-1.85)
Patenting per capita * Innovation-driven Binary			0.0171**
			(3.10)
_cons	4.037**	3.590*	2.984*
	(2.62)	(2.36)	(2.03)
N	797	797	775

Similarly, to Table 20, in Table 21 a similar effect is found, where all the standalone innovation variables are negatively correlated to GDP per capita growth. Albeit that only the coefficient for the regression including the binary term and the interaction is significant. The interaction term is also positive and statistically significant ($P<0.05$). Indicating that when using patenting as a proxy for innovation, it is found that innovation-driven countries experience more growth as a result from innovation than efficiency-driven countries.

Finally, Table 22, when using the researcher per 1000 employed proxy, once again shows a negative, statistically significant relationship between innovation spending and economic growth($P<0.05$). The interaction term between innovation-driven binary term and the measure of innovation shows a negative effect, this time, however. Indicating that when measuring using researchers per 1000 employed, Innovation-driven countries experience less economic growth as a result of innovating than efficiency driven countries.

Table 22: Random Effects Model Without First Difference Innovation-Driven Binary and Interaction (Researcher)

	(1) GDP per Capita Growth	(2) GDP per Capita Growth	(3) GDP per Capita Growth
researcherper1000 employed	-0.187***	-0.174**	-0.148**
	(-3.37)	(-3.18)	(-2.67)
Unemployment (%)	-0.0739*	-0.0761*	-0.0722*
	(-2.44)	(-2.54)	(-2.50)
Secondary School Enrollment (%)	0.0418*	0.0477**	0.0514**
	(2.31)	(2.65)	(2.88)
Net Migration per Capita (%)	-0.0000439	-0.0000424	-0.0000571
	(-1.37)	(-1.33)	(-1.80)
Urban Population (%)	-0.0294	-0.0261	-0.0252
	(-1.89)	(-1.73)	(-1.80)
Net Imports (%GDP)	0.0782***	0.0714**	0.0676**
	(3.32)	(3.09)	(3.02)
Innovation-Driven Binary		-0.511	-0.351
		(-1.20)	(-0.86)
Researcher per 1000 * Innovation-driven Binary			-0.825**
			(-2.84)
_cons	2.604	2.194	1.698
	(1.55)	(1.34)	(1.06)
N	797	797	775

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In this regression it is observable that for all three of the innovation proxies the interaction between them and the innovation-driven binary is insignificant, which is consistent with the regressions that were ran using first differenced variable and means that there is not enough evidence to suggest that a different economy development stage leads to experiencing higher (or lower) growth.

Conclusions & Discussion

To purpose of this research was to seek an answer to: "**How does the effect of innovation on economic growth change with time and economic development stage"?** In order to answer this question an extensive dataset was constructed using data from the OECD and the World Bank. This allowed me to apply panel data models to 39 countries spanning 31 years.

While some models were more successful than others in predicting an association between economic growth and per capita GDP growth, besides the random effects using non first differenced variables. From this the consensus of this paper seems to concur with the literature, that innovation has a positive effect on economic growth.

However,this paper sought not to investigate, like many others, how economic growth is propelled, and what role innovation has in doing so. Instead, this research aimed to fill in the gaps of the recent economic growth literature by investigating how this innovation economic growth relationship has altered over the years. Its secondary objective was to see how effectively innovation leads to economic growth for countries in different economic development stages, this is especially relevant now as we are amid an increase in globalization and what some call the digital industrial revolution.

While testing the first hypothesis: ***H1: the effect of innovation on economic growth diminishes over time.*** First differenced variables were used in a fixed effect model to account for the non-stationarity, there was a consistent sign and magnitude using all three proxies of innovation prior to adding the interaction term with time, for which R&D per capita spending and Patenting per capita were highly significant. Countries that innovate more, experience more per capita growth.

However, when the interaction term between innovation and time was added, the independent variable as well as the interaction term become insignificant for R&D per capita spending and Patenting per capita. A reason for this might be because the interaction term may be accounting for some variation that attributed to R&D per capita spending, which then makes the latter less significant. Furthermore, it might highlight that the introduction of time is simply not enough to account for the complexity of innovation, and other variables are likely to confound this relationship. The researcher concentration model, however, had very significant results after adding the interaction term, suggesting that increasing researcher concentration leads to higher per capita GDP growth, which is diminishing over time.

The models were originally run with the variables that contained unit roots as first differenced, this was done to ensure that there was no form of unknown trend that could make any relationship that is being established inaccurate. However, since the first hypothesis entails changes in time, this might not be vital for obtaining unbiased results. Therefore, as a robustness test, the models were also run with their original values. This has an additional benefit of containing more data, when running the models without the first differenced variables, the results obtained were all highly significant($P<0.01$). Both for the innovation proxy and the interaction term. This reinforces evidence to confirm the first hypothesis; while innovation increases GDP per capita growth, this effect diminishes over time. This, however, has led to a situation in which the preferred model using first differenced variables, that is less likely to be biased, but contains less information can only accept ***H1*** when using researchers per 1000 employed as a proxy for innovation. Whereas the models with different variable specification that acted as a robustness had results in which all proxies showed significant results both before and after adding the interaction term. As a result, ***H1: the effect of innovation on economic growth diminishes over time*** may only be partially accepted.

Testing the second hypothesis: ***H2: The effect of innovation on economic growth will be stronger for innovation- driven economies than efficiency-driven economies.***

A fixed effect model was no longer appropriate due to the incorporation of time invariant fixed effects, in the form of a binary variable with the value *one* for innovation-driven economies, and *zero* for efficiency-driven economies. These countries were classified using a table provided by the GEM, this was used in a random effect model. The coefficient of the binary variable for every proxy of innovation had a negative sign. Indicating an opposite effect than originally hypothesized, this, however, was not statistically significant at any significance level($P>0.05$), indicating that there is not enough evidence to suggest that innovation-driven countries experience less or more economic growth than efficiency-driven.

After the introduction of the interaction term, the results for R&D and patenting as a proxy for innovation were significant. The coefficient for R&D spending per capita had a positive sign, and the coefficient for the interaction negative. This means that countries that invest more in R&D or patent more are more likely to experience higher economic growth, and this is more so the case for efficiency-driven economies than innovation-driven economies. One explanation for this might be that innovation-driven economies are more likely to be more advanced. This means that the mechanism of oversaturation of innovations might be more powerful than the factors of innovation-driven countries that bolster innovation, and growth from innovation, inhibiting these innovation-driven economies' growth rates. None of the results were significant for the researcher per 1000 employed.

Lastly, using the original variables rather than first differenced variables yielded significant results, for all regressions including interactions($P<0.05$). Using R&D and patenting as proxy found a positive interaction term between innovation-driven countries and economic growth, while researchers per 1000 employed was negative. The fact that a lot of the results contradict each other makes accepting the hypothesis problematic, instead, it is weakly rejected since the preferred model had two proxies in which efficiency-driven countries were statistically significantly experiencing more growth as a result from innovation.

Limitations & Suggestions for further research

1. **Data:** While the data nowadays is superior to what was available during the period of peak interest in economic growth literature. It was still not complete. The datasets

contained missing data, which had to be manually interpolated. This might lead to inaccuracies in the data, for example, if data was missing during a year of economic disaster for example, the interpolated data could be wildly different to the real unrecorded data. Moreover, if there are datasets available with more countries other than the OECDs, for example, preferably factor-driven countries. The second hypothesis could have been tested with a categorical variable for each type of economy, and differences could have been observed between all three. Finally, it is worth nothing that there are countries that have had more missing observations than others. It is also possible that this missing data could by systematic, for example, occurring primarily in the first few years of the study period, if those years had much higher or lower growth rates than the later years, it could lead to the established coefficient between innovation and time to be inaccurate. The research could therefore benefit from an improved sensitivity test, ensuring robustness of the results.

2. **Causality:** While a negative association is found between researchers per 1000 employed and economic growth over time for the models with the first differences, and statistically significant negative associations for all innovation metrics in the model without the first differenced variables, it is unlikely that this is a causal effect. The reason for this is that there are countless factors that could affect economic growth. In this research setting especially, there are for example, unobserved factors such as government policies, cultural, social and economic conditions, natural disasters, using a fixed effects model helps remove the differences that countries might have by eliminating the individual-specific time-invariant factors through time de-meaning each variable, this means that the concern about the unobserved heterogeneity is no longer problematic. However, this does not remove concerns about the idiosyncratic shock, or the time variant components. Some unobserved time variant components might be trade agreements (this was attempted to be accounted for by controlling for net imports), but also, as previously mentioned, government policies and cultural changes. It is therefore possible that better models might exist. One such model is the general

method of moments technique, which is often used in this type of research (Ulku (2004), Levine et al. (2000), Hasan & Tucci (2010)). This model is specifically designed to address endogeneity issues that might occur. This research would therefore improve its robustness by incorporating such a model. Moreover, it must be acknowledged that most of the OECD countries are developed, European nations, if the dataset had a larger variety of countries by including for example more Asian, African, or South American countries. The research would be more all-encompassing. Perhaps while testing the second hypothesis with a larger variety in countries, an improved effect could be found.

3. Reverse causality: While the relationship between innovation and economic growth might seem straightforward in that countries that innovate more grow more. There might be other factors unconsidered, for example, it is entirely possible that countries with more money to spend have more to invest in innovation. While the focal point of this paper was not whether or not innovation affects economic growth, this is still an important point to consider. One way in which further research could improve this paper is by using an instrumental variable model to isolate the exogeneity.
4. Time lag: Another issue that might be present in this research is that there might be a discrepancy between the investment in innovation, through R&D investment, patenting per capita or researcher concentration, and the results to per capita GDP growth. This means that any coefficient might be inaccurate because of the way that panel data settings, the fixed and random effects are comparing the effect of innovation on economic growth for each year, while in reality the results of the innovation might only be realized years later. Whether this is because of factors such as R&D being a long process, or the fact that adding extra researchers does not instantly lead to more innovation. This research could benefit from other models that could account for time lags.
5. Independent variable specification: While the GEM has assessed many factors in their classification of countries, in the end, the ranking is still subjective, and the importance on specific factors might not be the same for everyone who categorizes these countries. Similarly, measuring innovation, as previously mentioned, is an unattainable objective.

Each proxy has its own advantages and disadvantages. Perhaps this research could benefit from a compound variable that combines all the innovation within a country and summarizes it in one variable. That way the results would be more consistent and simpler to interpret.

There is also a limitation when it comes to the independent variable for the economy classification. Countries can transfer from one economic development stage, and while the signs point towards this being a quite drawn-out process, it is possible that some shifts might have happened in the roughly 30 years of this dataset. This might impact the accuracy of the regressions since a country could theoretically have spent a majority of the 30 years in one stage but be marked down as another stage. Having a detailed list of countries' economic stage with economy stage classifications for each year would have benefitted this research. That way countries could have time varying economic development classifications.

Implications

Revisiting the literature on the relationship between innovation and economic growth was necessary due to the changes the global economy has experienced. The increased interconnectedness of countries, technological advancements that some refer to as the fourth industrial revolutions, and the growing importance of data, have changed the economic landscape. This therefore requires a reevaluation of past findings. Through the availability and access of superior, more comprehensive data a new association was explored, that being the effectiveness of innovation over time, and the importance of innovation between two different economic stages.

While the first hypothesis was not strongly accepted, through the researcher proxy, and the models in which first differences were not applied, there was evidence of the effect of innovation diminishing over time. From a practical standpoint this could assist policy makers in the sense that they should not over promote innovation, and be considerate of timing, and the saturation of innovation in their economy. Moreover, since there was no significant effect found between innovation-driven and efficiency-driven economic stages on the effect of innovation on growth. Efficiency-driven economies must not fall into the trap of over investing into innovating itself, but perhaps focus on policies to create an atmosphere in which innovation can thrive, for example, policies to improve education or infrastructural developments.

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Appendix A

Figure 1: line plot patent per capita (million) and R&D costs per capita($) for Countries with high GDP

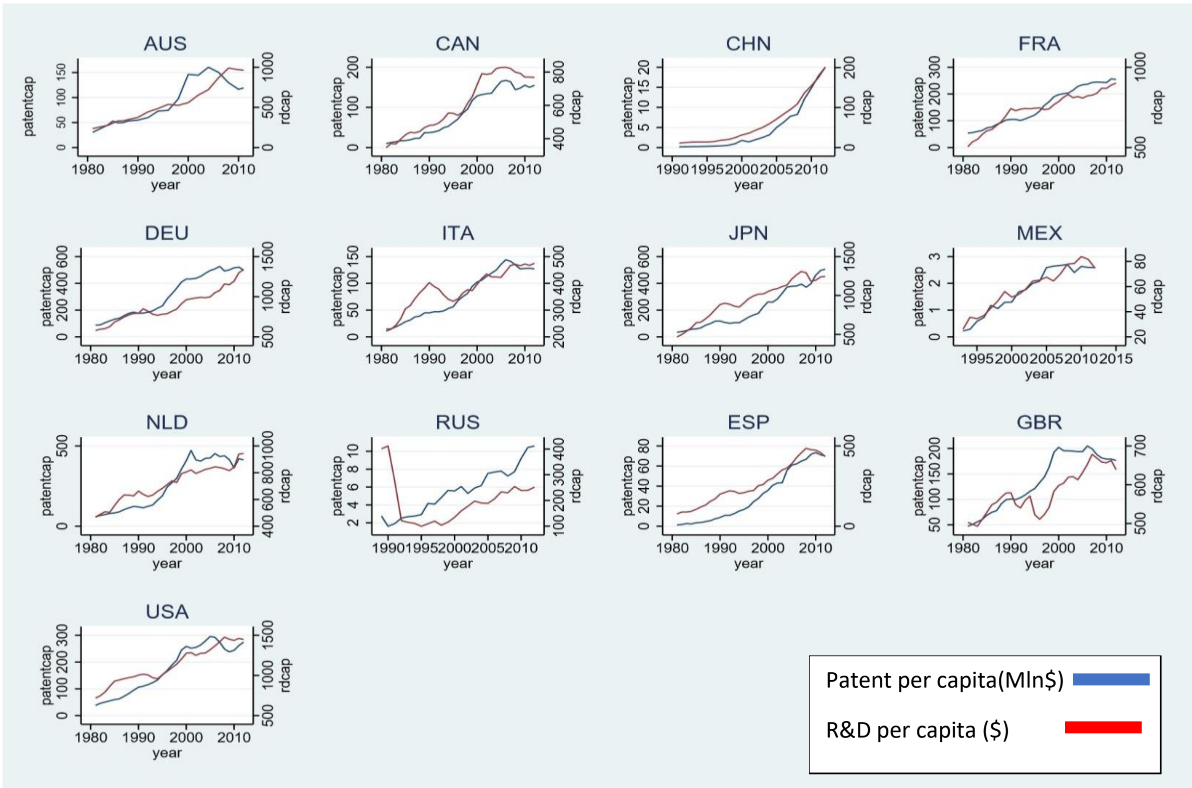

Figure 2: line plot patent per capita (million) and R&D costs per capita($) with small GDP

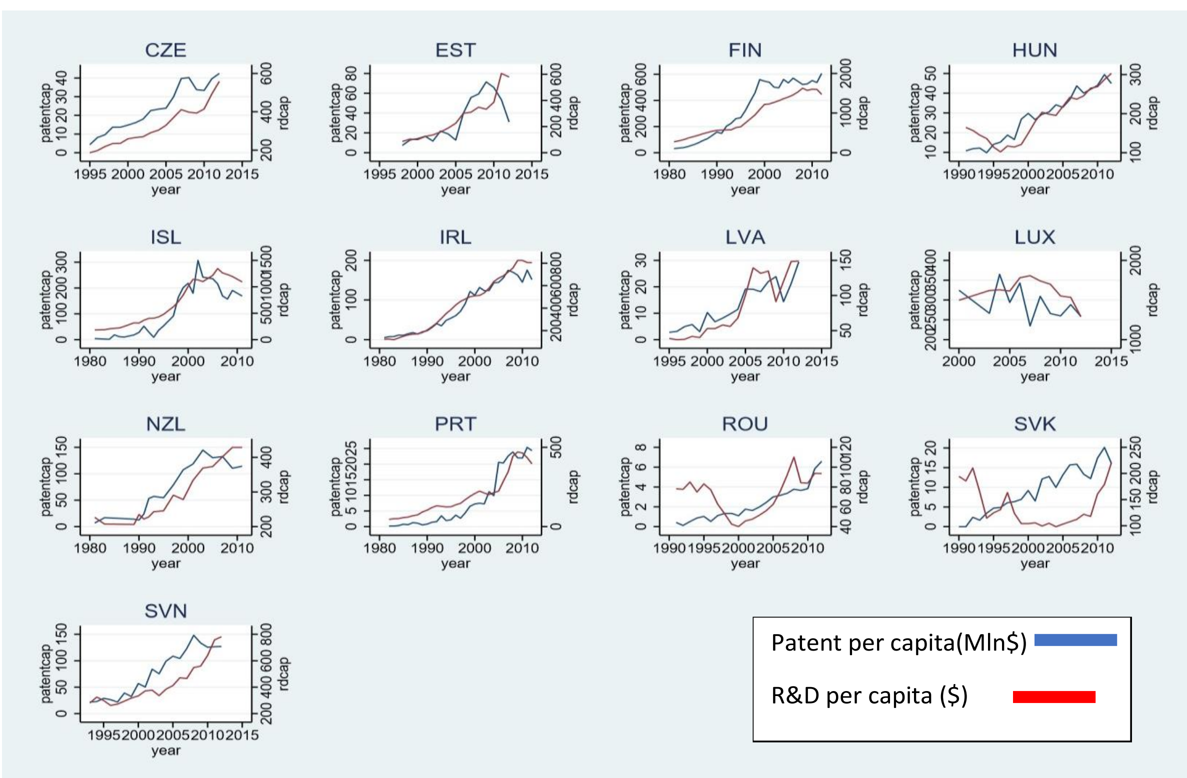

Figure 3: line plot patent per capita (million) and R&D costs per capita($) for high GDP per Capita

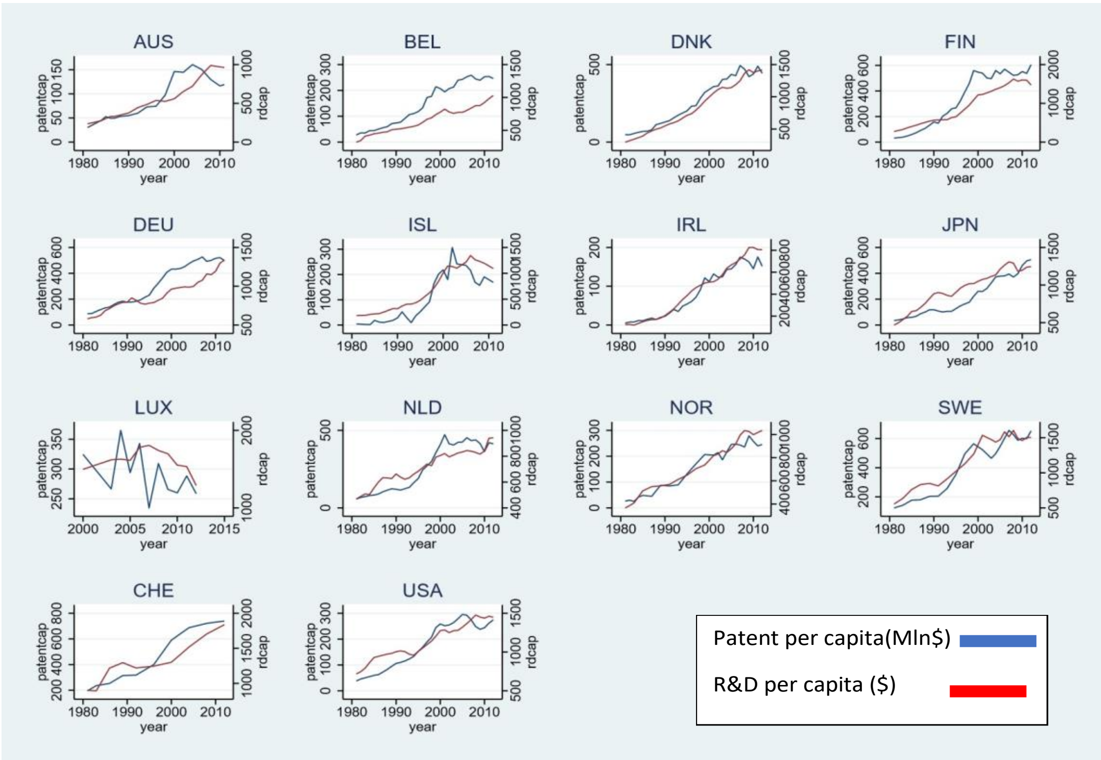

Figure 4: line plot patent per capita (million) and R&D costs per capita($) for low GDP per Capita

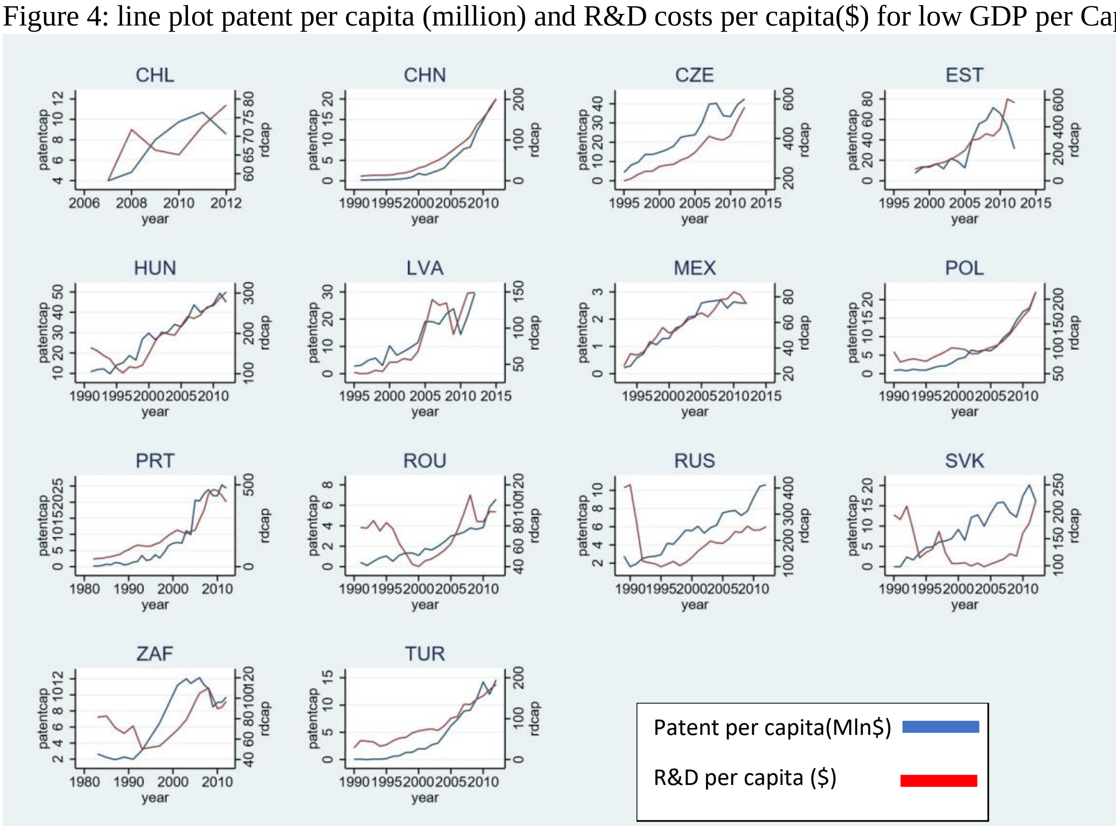

Figure 5: Country Categorization Provided by the GEM.

Table 2: Countries/economies at each stage of development

Stage 1: Factor-driven (37 economies)	Transition from stage 1 to stage 2 (16 economies)	Stage 2: Efficiency-driven (30 economies)	Transition from stage 2 to stage 3 (24 economies)	Stage 3: Innovation-driven (37 economies)
Bangladesh	Algeria	Albania	Argentina	Australia
Burkina Faso	Angola	Armenia	Bahrain	Austria
Burundi	Azerbaijan	Bulgaria	Barbados	Belgium
Cambodia	Bhutan	Cape Verde	Brazil	Canada
Cameroon	Bolivia	China	Chile	Cyprus
Chad	Botswana	Colombia	Costa Rica	Czech Republic
Côte d'Ivoire	Gabon	Dominican Republic	Croatia	Denmark
Ethiopia	Honduras	Egypt	Hungary	Estonia
Gambia, The	Iran, Islamic Rep.	El Salvador	Kazakhstan	Finland
Ghana	Kuwait	Georgia	Latvia	France
Guinea	Libya	Guatemala	Lebanon	Germany
Haiti	Moldova	Guyana	Lithuania	Greece
India	Mongolia	Indonesia	Malaysia	Hong Kong SAR
Kenya	Philippines	Jamaica	Mauritius	Iceland
Kyrgyz Republic	Saudi Arabia	Jordan	Mexico	Ireland
Lao PDR	Venezuela	Macedonia, FYR	Oman	Israel
Lesotho		Montenegro	Panama	Italy
Madagascar		Morocco	Poland	Japan
Malawi		Namibia	Russian Federation	Korea, Rep.
Mali		Paraguay	Seychelles	Luxembourg
Mauritania		Peru	Suriname	Malta
Mozambique		Romania	Turkey	Netherlands
Myanmar		Serbia	United Arab Emirates	New Zealand
Nepal		South Africa	Uruguay	Norway
Nicaragua		Sri Lanka		Portugal
Nigeria		Swaziland		Puerto Rico
Pakistan		Thailand		Qatar
Rwanda		Timor-Leste		Singapore
Senegal		Tunisia		Slovak Republic
Sierra Leone		Ukraine		Slovenia
Tajikistan				Spain
Tanzania				Sweden
Uganda				Switzerland
Vietnam				Taiwan, China
Yemen				Trinidad and Tobago
Zambia				United Kingdom
Zimbabwe				United States