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The divide between East and West: A comparative innovation study in Europe using traditional and new indicators

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Abstract

Innovation is a very important factor for economic growth and more countries than ever are looking to improve their innovation capabilities. But to improve innovation, proper policy is needed and there must be a way to measure innovation properly in every economy. This thesis compares the innovation between Central and Eastern European (CEE) countries and Western European countries. This is done using traditional and new innovation indicators because new indicators can measure more innovation in the CEE countries, allowing for a fairer comparison. CEE has had enormous growth following its entrance to international markets when a lot of foreign direct investment (FDI) entered these economies. However. After the economic crisis of 2008, the level of FDI dropped and their growth slowed, to grow these economies in the absence of FDI more focus should be put on innovation to keep these economies growing. The problem with measuring innovation in this region is that a lot of innovation happens without patents or in the absence of large R&D investments. So, it is important to have indicators that can properly measure innovation in this region to create a proper comparison with the West. Using multiple fixed-effects regressions this thesis has analysed the relationship between various traditional and new innovation indicators in CEE countries and compared these results to the full sample including Western and CEE countries. These regressions were performed on a panel dataset containing 11 CEE countries and 6 Western European countries starting in the year 2008 up to 2020. The results indicate that traditional innovation indicators measuring the number of patents and R&D investments have higher coefficients for Western European countries than CEE countries. The new innovation indicator high-tech exports has a higher coefficient in CEE nations compared to Western European nations. These results still hold up when these indicators are combined into a model, but these differences are insignificant. This suggests that when comparing innovation in CEE countries to Western countries the relationship of innovation indicators is not significantly different across these regions.

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1. Introduction

Economic growth is a crucial element in the development of a nation and the prosperity of its people. This is usually paired with a rise in production and consumption and this growth is measured with indicators like GDP. Today with the higher use of technology changing the economy faster than ever stagnation in growth can have bigger effects on job opportunities and poverty. Schumpeter already coined the term creative destruction where technological advances are the main source of economic growth, the innovation of new products or processes destructs the existing ones in the process (Galindo & Picazo, 2013). Romer also developed a version of the endogenous growth theory. where innovation is the main driver of growth by creating new products that are not necessarily improved (Howitt, 2010).

Because of its significant effect, a lot of high-income countries are knowledge-driven economies and are innovation-based. Joffe (2011) explains that in high-income capitalism the economy is innovation-based and characterised by new and higher-quality goods and production methods. As more countries around the world are becoming increasingly more developed, the rise in world trade allows less developed countries to participate and grow their economy at a rapid pace. This increasing number of high-income countries around the globe makes innovation more important than ever and requires proper innovation policies in these countries to be successful.

A group of countries that are starting to join the global innovation chains are Central and Eastern European (CEE) countries. In the 1990s their economies switched from planned economies to an open market, a result of this was that a lot of foreign direct investment (FDI) entered these economies. Foreign companies made these investments because wages were low in this region and their economies grew quickly. But after the financial crisis of 2008, much of this FDI was cut back and the growth rate in CEE countries decreased sharply because their economies were vulnerable to outside shocks. To combat this CEE nations are trying to rely less on FDI to grow but also started to focus on innovation to create growth from within the country which is the most viable way to sustain growth in a future with less FDI. So, it is interesting to compare the CEE nations that have more recently started focussing on innovation to see what different effects innovation indicators give when these countries are compared to Western countries.

But to know how much innovation is happening so countries can be compared, the level of innovation must be measured and since innovation is a process that is comprised of many factors that can be vastly different across firms, it is difficult to measure. For example, Artz et al. (2010) researched the relationship between R&D spending and firm output and found that more R&D spending indicated that more patents were filed, and new products were announced. R&D and patents are examples of traditional input innovation indicators and are often used because there is clear a link between spending on R&D and filing patents that give innovation as an output. So, a good first step Eastern European countries have taken is to use traditional indicators to measure innovation. But these science and technology indicators that are comparable were originally initiated by the Organisation for Economic Co-operation and Development (OECD) in 1963 and various member countries have tracked these statistics and produced reports regularly since then (OECD, 2015). But the OECD members at that time were already industrialised countries so these indicators might not explain the level of innovation in Eastern Europe properly which can hinder the ability to compare CEE countries to Western countries.

This thesis will aim to use indicators traditional indicators and indicators other than R&D and patents to measure the link between innovation and economic growth in CEE countries and compare it to Western countries by looking at the relation of the different indicators to GDP which will be used as a proxy for growth. The following research question will be used to answer the thesis:

Do indicators other than R&D and patents show different levels of innovation in CEE countries and does this effect differ from Western European countries?

This question will be answered by delving into multiple topics concerning innovation and growth which will be explored in the theoretical framework and then hypotheses are formed. The hypotheses will be tested by using linear regressions. The regressions will be performed on a database that is constructed of data from CEE countries that are in the EU and a couple of Western nations that are in the EU over a period from 2008 until 2020. This period gives a good view of the level of innovation that happened after the recession when FDI declined sharply in CEE countries. The expectation is that the results will show that the effect these indicators show will differ between Western and CEE countries and that traditional indicators will have smaller coefficients and new indicators less small or even larger coefficients.

These findings can help policymakers make better decisions regarding innovation policy in CEE nations. By identifying the relationship between R&D, patents, and new indicators with growth the most relevant indicators for these economies can be found and the level of innovation in a country will be more accurately represented. These better innovation policies can allow for more growth in these economies and bring more prosperity to the people. Finally, it can give new insight into the relationship of certain innovation indicators to growth and how this differs between Western and Eastern European nations.

2. Theoretical Framework

To answer the research question multiple key concepts will be reviewed and hypotheses will be formed based on these concepts. First, there will be a focus on how innovation is linked to growth. Next, traditional innovation indicators of R&D and patents will be discussed and how they are linked to innovation and growth. In the third part, different innovation indicators will be discussed to see the viability of nontraditional indicators and why these indicators might be better for economies that are not fully developed. The final part will look at previous innovation research in Eastern Europe to show the current state of research. At the end of each concept, a hypothesis will be presented that will help answer the research question.

2.1 Innovation and growth

Innovation has already been linked to growth for a long time and has been researched by a lot of economists. Solow (1957) was the first person to add any type of innovation to a growth model. In his original model in 1956, he used population increase as an explanation for the growth rate after the labour and capital were in a steady state but incorporated the technological aspect a year later and the growth factors became: labour, capital, and technology. It is good to note that in this model there are no factors that explain the technological progress, just that the technological progress sets the growth rate in a steady state.

The next big step in linking innovation to growth came from Romer (1986) who made big contributions to endogenous growth theory. He presented a model where the positive growth rate stems from endogenous technological change that is driven by the accumulation of knowledge instead of the exogenous technological change that is unexplained in the model of Solow. A couple of years later another paper is released by Romer (1990) and he adds an explanation for the source of technological change in the model. Here the innovation sources are split into human capital and technological change and a research sector in the economy is identified. Adding R&D to the growth model granted new insights as to how investment in knowledge and innovation can cause growth. Aghion and Howitt (1992) also expanded on the endogenous growth model by linking it to creative destruction. In their model growth comes exclusively from technological advancement and each new successful innovation makes the old one obsolete, so patents are very important in this paper so the inventors can collect rents. The positive relation between innovation and growth that has been found has had the effect that research after this point will usually make use of R&D or patents on the effect on growth. The papers that analyse this effect will be shown in the next section where the origin of these indicators will be shown and how they are used.

2.2 Traditional indicators and growth

The first surveys that measured innovation were done in the 1920s and collected data from the USA, the UK and Canada and were limited to collecting R&D data. And in the 1950s the NSF (National Science Foundation) started doing an industrial R&D survey in the USA where besides R&D data also data on patents started being collected (Arundel & Smith, 2013). The next leap in measuring innovation was done by the Organisation for Economic Co-operation and Development (OECD). The member countries started collecting innovation data around 1960 but they encountered difficulties when conducting R&D surveys that made international comparisons difficult so there was a need for standardisation. In the following years, meetings were held to study the problem of measuring R&D and eventually, the Frascati Manual was released in 1963 by the OECD which had standard definitions of R&D that could be used in surveys by member countries (OECD, 2015). This was the first time in history that an R&D survey was comparable across countries. The Frascati Manual has gone through multiple versions and the newest is the seventh edition that was released in 2015. Over the years the manual has expanded its definition of R&D by identifying a lot of different parts of R&D expanding to human resources and updating categories to accommodate more modern technologies like software, but it is still mainly R&D focused. Arundel and Smith (2013) further explain that the Frascati Manual indeed does recognise that R&D is one of many factors that influences innovation and that there are other input and output measures for innovation.

The answer to this problem came in 1992 when the European Union (EU) introduced the Community Innovation Survey (CIS). This survey asked questions that went beyond traditional indicators like R&D and patents, covering more processes that are related to innovation (Eurostat, 2021). This survey is based on the Oslo Manual which like the Frascati Manual is a reference guide on how to collect and use innovation data. This survey is used for EU national policy reports like the European Innovation Scoreboard (EIS), which ranks countries based on various innovation indicators as an Innovation leader, Strong innovator, Moderate innovator or Emerging innovator. However, most of these indicators are still measuring a form of R&D and a lot of the current research relies on R&D or patents as proxies for innovation because the data is most widely available for these indicators.

Pradhan et al. (2020) delve into the effect of innovation and entrepreneurship in 19 Eurozone countries. The innovation indicators used are traditional and mostly directly related to patents and R&D and analyse their effect on per capita growth and a couple of entrepreneurship indicators. It is found that innovation and entrepreneurship promote long-term growth but that the short-term results vary. the empirical results suggest that it is important to have a good ecosystem for entrepreneurship and innovation and to achieve this business-friendly policies should be put in place and R&D and technological capabilities should be upgraded. But the individual indicators are not deeply analysed.

Capriati (2021) performs a regional analysis of links between innovation, human development and growth. Innovation is split into two parts: the creation of technology by using R&D and patent data and looking at the development of human skills by using the population with tertiary education and human resources in science and technology. The results show that there is a mutually reinforcing relationship between innovation, human development and growth and that these effects cross over into neighbouring regions. The implication is that all these variables should be promoted at the same level.

Pala (2019) researches innovation in developing countries which mostly are in South America or Central Asian or Eastern European countries. And uses traditional innovation indicators like R&D expenditure, employees in R&D and the number of patents as proxies for innovation in a random coefficient model. It is found that spending a larger percentage of GDP on R&D hurts growth and the number of people working in R&D has a slight positive effect.

Liu (2016) combines multiple facets that cause innovation: Intellectual property rights, R&D and FDI. These indicators are linked to growth in countries across all income levels to show how multiple innovation indicators act across countries at different development stages. The empirical results provide evidence for the fact that R&D. FDI, openness to trade, human capital and patent protection have positive effects on economic growth. Interestingly, R&D is key to growth in higher-income countries while FDI is behind a lot of the growth in higher and middle-income countries.

Hasan and Tucci (2010) analyse the effect of patents on growth in 58 countries across different income levels by performing multiple regressions. They find that countries with higher patent activity as well as primarily filing patents in the US has a positive effect on growth rate. The effect is also bigger for high and upper-middle-income countries compared to lower-middle and low-income countries. The positives and negatives of using patent data for innovation are also discussed. Patents are good for measuring innovation because they are public, and the records are well kept so there are large databases available with a lot of background information. Patents represent a form of innovative output and can be linked to R&D activity. The negatives of using patents will be discussed in the next section.

Coccia (2009) makes an interesting contribution by analysing if there is an optimal amount of R&D investment a country can make as a percentage of the GDP. The countries that are used are all EU members, candidate countries, Iceland, Norway, Switzerland, Japan, and the USA. It is found that Gross domestic expenditure on R&D (GERD) as a percentage of GDP is a crucial driver for productivity growth and that it explains 65 per cent of the variance in said growth. More importantly, GERD investments have diminishing returns and the optimal rate of R&D investment is between 2,3 and 2,61 per cent and maximises productivity growth in the long run. For example, the EU has a target of investing 3 per cent of its GDP into R&D (Rakic et al., 2021). Moreover, the composition of GERD is also very important, over 60 per cent has to come from businesses and about 30 per cent from the government. As the current research shows, when researching innovation using traditional indicators like R&D and patents as proxies is still very prevalent.

2.3 New innovation measures

The previous section concludes that most of the current innovation research still uses traditional indicators to proxy innovation, but these indicators are more suited for fully developed economies and might not explain the amount of innovation in CEE countries properly. There is indeed R&D and patenting going on in these economies and there probably will be a positive relationship between traditional indicators and growth so while the traditional indicators are useful for the CEE countries there are some shortcomings.

The first shortcomings that will be discussed are the ones concerning patent data. The negatives are that many inventions cannot be patented like an organisational process. Some entities also specifically choose not to patent even if it is possible, because patents are public, and they do not want their competitors to see their invention (Cohen et al., 2000). Another big problem is that patenting varies wildly per industry. For example, technology and machinery have more patenting than food products construction (Dernis et al., 2016). This can make it seem that countries which have a lot of industries that have a low propensity to patent have a lower innovation figure.

Dodgson and Hinze (2000) also give similar concerns about using patents as an innovation indicator. The propensity to patent also varies across firms and industries and not all inventions are patentable. In software, for example, there are a couple of areas where patents are irrelevant. Firms also do not patent everything as a patent is public which means your competitors can see your invention. A patent by itself does not say anything about its economic value or the use of the invention. Although, the fact that a firm went through the process of patenting means that they see value in the patent.

These problems are also mentioned by Lugones and Suarez (2010) who developed a document for the United Nations about innovation indicators and policymaking. They mention that the innovation process does not always end in a patentable product. Small location-specific changes to existing products which may not be patentable can have a profound effect on development which are not visible in patent statistics. To be able to compare patents across countries only databases that have patents of many different countries can be used and this has the result that the patent offices of the United States and Europe Union are mainly used, leaving out innovation that that is registered in a more local patent office.

These problems show themselves when patent data is used to measure innovation in CEE countries. The main issue mentioned previously is that patents show more industries have a high propensity to patent in a certain country. More developed economies like the Western nations with many high-tech companies that develop computers and machines seem to have much higher innovation than economies in the CEE region that are more based on food or mining. Thus, using patents as a proxy can make it seem that there is little innovation happening in CEE countries because industries in those countries are usually less likely to patent.

Another indicator that can have problems measuring innovation is R&D expenditure. Raghupathi and Raghupathi (2017) found that while in general R&D investment is an important indicator of innovation, only some OECD countries increase their innovation by having a higher R&D expenditure. While other OECD members promote innovation through spillovers from other countries and use the information generated by R&D investment in other countries to innovate. This still makes R&D investment an important factor, but it means that the R&D investment indicator only captures direct investment and does not measure innovation that occurs through spillovers.

Kleinknecht et al. (2002) also state some weaknesses of using R&D as an innovation indicator. The first problem is that R&D is an input of innovation which can be used efficiently or inefficiently. So, it does not say anything about the actual innovation in the scene of new products or processes. Secondly, R&D expenditure only accounts for one-fourth of the total expenditure when developing a new product. This means it is important to also account for non-R&D investments like investment in fixed assets, training of employees and market analysis. Lastly, a big issue they find is that the share of innovation expenditure is much higher for manufacturing than for services. This has the result of showing a 'manufacturing-based' result when using R&D as an innovation indicator.

The problems mentioned here make it harder to use these indicators in CEE nations. Because traditional indicators were based on the developed nations that created these indicators to measure their innovation in the first place. Then there was more standardisation by OECD and Eurostat to make better comparisons for their member countries which were developed nations. As these traditional measures have been used for a long time, they have gained legitimacy. Developing countries have difficulties challenging these indicators and most countries end up accepting these indicators and using them for policy without considering if these indicators do properly explain innovation in their countries. It is also noted that in less developed economies the share of firms that innovate without

R&D is higher and knowledge is amassed by purchasing machinery and equipment from abroad and using these new technologies to innovate this can be seen as innovation happening through spillovers or investing in fixed assets instead of R&D expenditure. Another problem is that in developing economies a large part of R&D is carried out by governments and universities and not businesses (Hollanders & Iizuka, 2017). For example, in Brazil firms were responsible for 38,2 per cent of the R&D spending and the government for the other 60,2 per cent. This is in stark contrast to the USA where 68,4 per cent came from the firms and 27,1 per cent from the government (Marins, 2008). This also aligns with the optimal R&D spending for a country where about 60 per cent should come from the companies and 30 per cent from the government.

To overcome these challenges in measuring innovation in developing countries numerous suggestions have been made. A solution to this problem made by Marins (2008) is to create new indicators that instead of measuring inputs like R&D or outputs like patents, measure aspects of how innovation takes place within firms. This is because firms in emerging economies have lower R&D spending and number of patents thus making traditional indicators biased against them. Indicators like innovation strategy, equipment, achievement capacity and technological maturity are suggested.

Hollanders and Iizuka (2017) have a very different approach to overcoming the challenges when using traditional innovation indicators in developing countries. They first suggest making the definition of innovation more inclusive for developing countries by shifting the nuance from being more productivity based to also including social welfare and sustainability. This way innovation processes and developmental goals of developing countries are more aligned with the definition of innovation. Secondly, they call for more understanding of innovation indicators in developing countries among policymakers and academia. This will make sure that policymakers understand what the indicators measure and if these are relevant for their country allowing for proper policy implementation.

An example of using an indicator to measure innovation that is not R&D or growth can be found in the paper by Schneider (2005). The paper researches the effects of Intellectual property rights (IPRs), FDI and high-technology trade on the rate of innovation and growth in developed and developing countries. The study finds that high-technology imports, stock of human capital, R&D expenditure and IPR protection are all important in explaining the rate of innovation. It is also interesting that foreign technology has a bigger impact on GDP growth than domestic technology. However, the major factors explaining innovation in developing countries are market size and infrastructure while high-tech imports, R&D and human capital have a stronger effect in developed nations.

2.4 Current research and background of innovation in the CEE region

To lay a foundation for the research of this thesis previous publications should be taken into consideration and some information on the background in the CEE countries will be given.

Eastern Europe experienced enormous growth after the collapse of the Soviet Union when countries that previously had a planned economy transitioned to capitalism. The poverty level rose at the beginning and 12 per cent of the population in central east Europe and the Baltics and 30 per cent of the south-east European states were living under the international poverty line (Izyumov, 2010). Just after the fall of the Soviet Union most of the Eastern European countries were classified as lower-middle income by the World Bank, meaning that their GNI was between $1086 and $4255 in 1992. The exact World Bank classifications can be found in the appendix.

However, this quickly changed because many investments were made in the form of FDI since these economies became more open. The main motivator for all this investment was the low labour cost in the region and firms started doing vertical FDI expansion of their supply chains (Popescu, 2014). This has allowed Eastern European nations to catch up and grow their economies rapidly. Thus in 2007 most of these countries were at least upper middle income with a GNI per capita between $4256 and $13205; some even broke into the high-income threshold above $13205 per capita. But because their growth was so dependent on FDI their economies were also extra vulnerable to external shocks. So, after the crisis of 2008, these states started receiving less foreign investment and are now at risk of falling into the middle-income trap (European Investment Bank, 2018). The middle-income trap is explained by Larson et al. (2016) as a state where a country attains a certain income and gets stuck at that level. This is usually characterized by a country experiencing growth to a higher income level by having cheap labour and reallocating that labour from agriculture to export-driven high-productivity manufacturing. This is then followed by lower growth as the rural labour force shrinks and wages rise (Gill & Kharas, 2007). To combat this the growth models in Eastern Europe need to change from relying primarily upon FDI to a model that is based more on innovation to break the current development ceiling faced in many countries (European Investment Bank, 2018).

A big problem that is currently hindering innovation in this region is brain drain which entails that a lot of highly skilled individuals are leaving the country to go to Western Europe for better opportunities. This can be partly due to public policies that want to increase the number of qualified personnel, but not enough jobs are created in these countries for these qualified personnel to work (Lugones & Suarez, 2010). Because these are the individuals that are making the innovation happen, having a proper innovation policy that increases welfare is crucial to keep these people in the country by increasing innovation incentives and having spaces where this new qualified personnel can work and innovate. This increase in innovation can make these countries less reliant on FDI and even attract new FDI that is focused on more technological and scientific industries, accelerating their growth even more.

To give a better picture of the current level of innovation in this region the innovation levels of firms in Eastern Europe used by the European Central Bank will be shown here to give an idea of which share innovative firms have.

- leading innovators (i.e. those that develop products new to the country or the global market and report substantial R&D expenditures)
- incremental innovators (i.e. those that develop products new to the company and report substantial R&D expenditures)
- adopting innovation (i.e. those that report no substantial R&D expenditures and that develop products that are new only to the company)
- developing innovation (i.e. those that report substantial R&D expenditures, but that do not yet develop products new to the firm, country or global market)
- “basic” firms (with no substantial R&D expenditures and no development of new products)

European Investment Bank (2018) found that 4 per cent are leading innovators, 15 per cent are incremental innovators, 29 per cent are adopting innovators, 4 per cent are developing innovation and a staggering 48 per cent are basic firms. What is clear here is that a large part of these firms does not have a lot of R&D spending, and this could be explained by the fact that innovation in less developed countries more often happens without R&D but by purchasing equipment and transferring knowledge that way. This is an innovation that cannot be measured by traditional indicators like patents and R&D (Hollanders & Iizuka,2017).

This background information shows that the CEE region has had large growth after the 1990s and this growth has since slowed down. A good way to increase growth in the current landscape is to focus their growth model to be more innovation-based. It also explains that the current brain drain is a hindrance to achieving this innovation growth and that innovation in this region is mainly adopting innovation that occurs without substantial R&D investment. Next, some current research about this region will be discussed.

Petrariu et al. (2013) study the link between innovation and economic growth in CEE countries. The results show that R&D as a percentage of GDP and the number of patents have a significant effect on growth, but it is negative. The number of researchers also hurt growth. The study suggests that this is typical for the catch-up process these countries had rapid growth because many inventions were imported from more developed countries there was less interest in domestic research.

Pece et al. (2015) perform a similar study researching the relationship between innovation and growth in Poland, the Czech Republic and Hungary and perform regressions on each country individually. The results show that the traditional innovation indicators have a positive effect on growth, but that FDI has a more major impact on growth. Furthermore, it is found that education and human capital also have a strong impact on growth.

The Baltic states are also an important region in the CEE area to focus on. Pilinkienė (2015) has looked at R&D investment and competitiveness in this region. They find a positive effect of R&D investment on efficiency but note that R&D investment in this region grows slowly and lags behind the EU average and that the economies in the Baltic states mainly consist of low-technology industries, but it is noted that Estonia is the leader when it comes to innovation and competitiveness. The source biggest of R&D funding comes from the government and most of the government goes to high higher education. This is in contrast to countries leading innovation where the largest part of R&D investment comes from the business sector.

Paas and Ponte (2010) also researched innovation performance in the Baltic states. They state that according to the European Innovation Survey Estonia is a moderate innovator and Latvia and Lithuania are catching-up countries. The authors argue that due to missing data in Latvia, this classification can be biased to show less innovation. Furthermore, they say that the indicators used by this survey capture only some parts of the education system which could show a lower human capital level than is present. Their small economies also lead to the problem that they are highly dependent on a single enterprise in each sector, which causes indicators to be very volatile. They analysed SMEs in Estonia to demonstrate that non-R&D innovation expenditure was higher than the EU average while the share of firms that were able to reduce cost was below the average. This shows that non-R&D innovation is present, but firms do not utilise resources efficiently. The conclusion is that Estonia despite these shortcomings, is the biggest innovator in the Baltic states. This is the result of a policy that attracts foreign investors via a tax policy and being closer to Scandinavian countries. Finally, it is also emphasized that as the Baltic states move away from investment to innovation-based development, statistical indicators should be improved to allow for better measurement of innovation.

Kaneva and Untura (2017) researched innovation in a similar region, namely Russia where they have performed a regional analysis linking innovation to growth. Firstly, they find that the innovation has happened according to plans set by the government. Expenditure on technological innovation had the biggest positive effect on regional growth and it is interesting to note that the number of patents granted does not have a significant effect. The majority of innovation also takes place in larger hubs like Moscow or St. Petersburg and there are positive spillovers from these regions, but their effects are small. The regressions performed in this paper will be the basis of how this thesis will perform its data analysis.

2.5 Hypotheses

In this section the hypotheses will be constructed using the information from the previous sections of the theoretical framework.

Previous research leading back to Solow (1957) has shown that innovation is positively related to growth. While the technological change was initially unexplained, future models by Roemer (1990) contained endogenous technological change. The innovation in his model is explained by human capital, an R&D sector and technological change, leading to economic growth. Aghion and Howitt (1992) linked innovation to economic growth by using creative destruction as a source of innovation where previous technological advancements were displaced by new innovations and added an important role for patents that protected these new innovations. This research has shown that innovation is positively linked to economic growth in endogenous growth models and to test if these theories are also applicable to the dataset used in this thesis a hypothesis is formed.

H1: Traditional innovation indicators have a positive relationship with GDP growth.

To measure the relationship between innovation and growth indicators have been created. When innovation was first being measured countries found that they could not directly compare innovation data. The OECD came to a solution for this problem by releasing the Frascati Manual which contained standard definitions for innovation indicators which allowed member countries to compare innovation. This manual has been updated over the years to accommodate more modern forms of innovation like software. A lot of the current innovation research still uses these innovation indicators and positive relations are found between indicators like R&D expenditure and number of patents with GDP growth. However, it is found by Liu (2016) that R&D has a bigger effect on growth in higher-income countries compared to lower-income countries. Similar results are also found by Hasan and Tucci (2010) who say that the number of patents filed has a stronger effect on growth in higher-income countries. This could be because these indicators were created by already industrialised economies in the 1960s, so they do not find similar relations in lower-income countries. This finding leads to the second hypothesis:

H2: Traditional indicators show a stronger relationship with GDP growth in Western Europe compared to CEE countries.

Traditional indicators can have issues when trying to compare innovation between Western and CEE nations as they have smaller effects which could mean that less of the innovation in CEE nations is captured nations by traditional indicators. There are multiple causes for the difference in numbers when measuring innovation between Western and CEE nations. For example, multiple issues can occur when using patents as an innovation indicator. Firstly, not all inventions are patentable like an organisational process or certain forms of software. Some industries also choose not to patent because that would mean that their invention becomes public knowledge as patents are public and firms can prefer secrecy. The number of patents also varies wildly per industry as high-tech industries that develop computers and new machines in Western nations have a higher propensity to patent. This can cause issues when using patents to compare innovation between CEE nations and Western Europe as CEE countries will have fewer industries that are more likely to patent. Using R&D as an innovation indicator can also have problems when used to compare innovation between Western and CEE countries. Not all countries increase their innovation by having higher R&D expenditures some countries rely more on spillovers of R&D investment from other countries (Raghupathi & Raghupathi, 2017). When comparing innovation between Western and CEE countries this could be a problem as innovation in Western countries happens more with direct R&D investment while innovation in CEE countries occurs more via spillovers and purchasing equipment which cannot be measured by the R&D indicator. A solution to this problem is to also include innovation indicators that can capture innovation that happens without R&D investments and patents. Schneider (2005) has found a potential indicator that could solve this problem, high-technology trade. He finds that this is an important indicator for explaining innovation next to R&D expenditure, patent protection and human capital. To test if these indicators do measure innovation the following hypothesis has been created:

H3: New indicators of innovation are positively related to growth.

As these indicators should measure more innovation in CEE nations compared to Western nations due to the different sources of innovation because high-technology trade for example could have high-tech products included that were created via spillovers of knowledge and thereby adopting innovation instead of using R&D investment and patents. This leads to the following hypothesis:

H4: New indicators show relatively more innovation in CEE countries compared to traditional indicators.

3. Data

The following section will explain which data was used and offer more explanation for the variables that will be used in the analysis. The main dataset used for this study comes from Eurostat, which is the statistical office of the European Union. It contains data for all member states and some data also for European countries that are not in the EU. The span of the data is very wide containing various categories like economy, populations, and innovation. A couple of indicators were collected from the World Bank database which contains a large number of time-series variables mostly coming from the statistical systems of member countries. The European Patent Office (EPO) was used to collect data about patents and finally, a couple of variables were taken from UNESCO Institute for Statistics (UIS). The data from these datasets are combined to create a new panel dataset. In this data set the period that is researched is from 2008 – 2020. These years are chosen because these years show the period after the economic crisis when the amount of FDI in CEE countries dropped and it became more important to have innovation as a driver of growth to replace the growth that previously had mainly occurred because of FDI. Secondly, for several indicators there was little data available before 2008, this solidified the decision to analyse after 2008. The reason for 2020 as the final year is also similar, because for many variables the data only runs until 2020. The dataset contains 17 EU countries which are Eastern and Western European, the countries that will be used are: Austria, Belgium, Bulgaria, Croatia, Czechia, Estonia, France, Germany, Hungary, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Romania, Slovakia and Slovenia. Next, the variables used will be explained more in-depth.

3.1 Dependent variable

GDP and main components (output, expenditure and income)

The first dependent variable in this study will be the GDP of a country in current prices in millions of euros. These GDP values are not corrected for inflation as the other variables in the dataset were also not corrected for inflation.

The GDP of a country is chosen as the dependent variable because it has been used in many previous papers as a dependent variable as a proxy for economic growth in Eastern Europe. Kaneva and Untura (2017) use Gross Regional Product (GRP) as the main indicator of regional innovative growth when researching innovation in Russia. Also, a paper researching the effect of innovation on growth in the CEE region by Pece et al. (2015) uses GDP as a proxy for growth. Another research of innovation on growth in the CEE region by Petrariu et al. (2013) has used GDP growth as the dependent variable. This gave confidence in using this indicator as a proxy for economic growth.

3.2 Independent variables

The independent variables will be split into two sections. The first part will be the traditional innovation indicators that have been used thoroughly and the second part consists of the less-used innovation indicators that may show a better picture of innovation in CEE countries.

3.2.1 Traditional innovation measures

The R&D indicators are all collected via the methodology laid out in the Frascati Manual which was created by the OECD as explained in section 2.2. These traditional indicators have been chosen on the basis that they were created in the 1960s by the OECD and have been used by most of the innovation research from then until now as proxies for innovation and are positively correlated with economic growth.

Gross domestic expenditure on R&D (GERD)

The total expenditure on R&D measured in millions of euros.

GERD as a percentage of GDP

The percentage of the GDP that corresponds to the amount of GERD.

Business enterprise expenditure on R&D (BERD)

This is the total amount of funds spent by businesses on R&D measured in millions of euros.

Government budget allocations for R&D (GBARD)

This variable shows the total amount of money each government has allocated for R&D in government establishments, business sectors, private non-profits and higher education. This variable is measured in millions of euros (Eurostat, 2023c).

Number of patent applications to the EPO

The total amount of patent applications sent to the EPO by each country.

Number of patents granted by the EPO

The number of patents that are granted to each country by the EPO.

Number of R&D personnel as full-time equivalent (FTE)

R&D personnel is defined as all persons directly employed within R&D and employees supplying direct services like managers and clerical staff (Eurostat, 2023a)

3.2.2 New innovation measures

The following variables are based on classifications of the Statistical classification of economic activities in the European Community (NACE) which has classified economic activities since 1970. The NACE is currently in revision 2 and the sectors that make up each variable can be found in the appendix. These new innovation indicators are chosen as they can also measure innovative activities that happen without R&D and patents. This is fairer against CEE nations because innovation in those countries happens less with R&D expenditure but through spillovers and adopting innovation. Moreover, innovative activities in CEE countries are less likely to include patents. Employment and the number of enterprises in high-technology sectors achieve this by also being able to include innovative firms that do not have high R&D spending or patents. In this way, innovation can be compared more fairly between CEE and Western countries. The export of high-tech products can measure the output of innovative products that a country has that potentially could be created without R&D and patents and this can also help to make the comparison between CEE and Western countries fairer. The import of high-tech products can be a proxy for spillovers which can cause innovation in CEE nations that is not captured by R&D investment. Finally, the number of researchers can give a better idea of the total number of innovative people in a country that is not limited to working directly in R&D.

Employment in high and medium high-technology manufacturing

The employment in high and medium high-technology manufacturing shows how many people are working in these industries and will be measured in thousands of people.

Employment in High-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services)

This variable measures the employment in high-technology sectors in thousands of persons.

Employment in knowledge-intensive activities

This indicator measures the employment in knowledge-intensive activities in thousands of persons.

Enterprises in Medium high-technology manufacturing

The number of firms in medium high-technology manufacturing measured by NACE activity.

Enterprises in High-technology manufacturing

The number of firms doing high-technology manufacturing measured by NACE activity.

Enterprises in High-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services)

The number of firms in high-technology manufacturing and knowledge-intensive high-technology services measured by NACE activity.

These next variables are measured by The Standard international trade classification (SITC). This is a product classification of the United Nations (UN) that is used to classify exports and imports. The system is currently in revision 4 and this revision will be used. The exact classification of the groups can be found in the appendix.

Total export of high-tech products

The total export of high-tech products is measured by using the SITC classification and is measured in millions of euros.

Total import of high-tech products

The Total import of high-tech products is measured by using the SITC classification and is measured in millions of euros.

Number of researchers (FTE)

Researchers is defined as professionals engaged in the conception or creation of new knowledge (UIS). This variable is measured as the number of researchers per million inhabitants.

3.3 Control variables

Not all the GDP growth is explained by the innovation indicators, so several control variables are used. These variables are chosen based on an OECD study done by Bassanini and Scarpetta (2002) in which they look at the forces behind economic growth. One of the determinants they mention is research and development. This is the focus of this study so the other variables mentioned will be controlled for. First, they mention the accumulation of physical capital as a determinant of GDP a similar indicator of fixed investments is used by Kaneva and Untura (2017). To control for this first determinant of GDP the gross fixed capital formation variable will be used. The following determinant mentioned by the OECD study is human capital a similar variable to this has been used as a control variable by Pece et al. (2015) namely the share of the population with tertiary education in the total active population. To control for this second determinant the variable Persons with tertiary education will be used in this study. Next, inflation and international trade are also mentioned as being important determinants of GDP. So, inflation is directly included as a control variable and international trade will be controlled for by using the trade openness of each country as a variable. Lastly, unemployment has been used by many previous studies as a control variable when the effect of innovation on growth was researched so that is why it is also included here.

Trade openness

The trade openness is measured by a method used by the OECD (2011) in which the sum of exports and imports are divided by the GDP.

Harmonised index of consumer prices (HICP) annual rate of change (Inflation)

The HICP is a cost of goods and services index and uses a fixed basket of goods and services to track prices over time. From this data, an inflation figure is derived.

Gross fixed capital formation (GFCF)

This variable consists of resident producers' acquisitions minus disposables of fixed assets during a given period and certain values of non-produced assets are also added. The GCFC can be seen as a proxy for general investment in the economy. This variable is measured in millions of dollars.

Unemployment rate

The rate of unemployed people compared to the whole working force between the ages of 15 and 74. Unemployed person here is defined in line with the guidelines of the International Labour Organisation as someone between 15 and 74 who has no job during the reference week and could start work in the next two weeks and has looked for a job in the past four weeks (Eurostat, 2023).

Persons with tertiary education

Tertiary education is defined as levels 5 to 8 from the International Standard Classification of Education (ISCED). These consist of: Short-cycle tertiary education, Bachelor’s or equivalent level, Master’s or equivalent level and Doctoral or equivalent level. This variable is measured in thousands of people that are aged between 15 and 64 (Eurostat, 2023c).

3.4 Descriptive statistics

The next two tables show the descriptive statistics for CEE countries and Western Europe respectively. This is done to help understand the differences in innovation activity between CEE countries and Western Europe.

Table 1: Descriptive Statistics of CEE countries

Variable	Obs	Mean	Std. Dev.	Min	Max
gdp	143	106570.06	115162.56	14149.4	531925.7
gerd	143	1139.459	1370.267	84.882	7292.84
gerdgdp	143	1.09	.535	.382	2.565
berd	143	636.056	838.907	27	4582.277
gbard	143	428.038	468.572	28.644	2369.299
patentapplications	143	89.566	111.959	7	566
patentsgranted	143	36.378	49.639	0	278
rdpersonnel	143	30614.378	32933.445	5086	173392
researchers	143	2559.672	990.401	790.688	5054.713
hightechexport	143	4211.561	5333.251	179.3	26296.24
hightechimport	143	4587.067	4595.371	352.52	19565.71
enterpriseshighmanu	143	1131.266	1199.038	110	4319
enterpriseshightech	143	21785.622	25160.37	1958	133119
enterprisesmedhigh	143	4974.245	6489.823	371	25553
employmedhigh	143	254.866	263.098	11.1	966.6
employhigh	143	138.254	130.897	19.5	551.5
employknowledge	143	1130.433	1202.357	177.4	4822
inflation	143	2.301	2.525	-1.6	15.3
gfcfinvestment	143	54154.384	57165.995	6112.124	251196.59
tertiaryedu	143	1284.973	1530.003	255.2	6764
unemployedrate	143	8.54	3.723	2	19.5
tradeopen	143	1.141	.341	.499	1.756

Table 2: Descriptive Statistics of Western European Countries

Variable	Obs	Mean	Std. Dev.	Min	Max
gdp	78	1102944.3	1090442.6	39042.9	3479368
gerd	78	28235.779	30841.828	561.403	110025.41
gerdgdp	78	2.308	.613	1.119	3.455
berd	78	18848.635	20910.032	310.4	75830.4
gbard	78	8868.74	9761.387	167.871	37171.11
patentapplications	78	7857.744	8855.702	274	27328

patentsgranted	78	4417.359	5674.328	84	21192
rdpersonnel	78	221631.9	228806.79	4652	735584
researchers	78	4610.845	673.094	2824.308	5911.687
hightechexport	78	35233.364	29323.909	461.45	94744.27
hightechimport	78	27131.449	23708.576	938.53	83973.62
enterpriseshighmanu	78	2440.397	2854.359	10	8975
enterpriseshightech	78	60327.179	49155.014	1503	144825
enterprisesmedhigh	78	9191.987	9842.209	61	30020
employmedhigh	78	971.538	1389.668	1.6	4198.8
employhightech	78	581.796	615.348	7.2	2219
employknowledge	78	5254.655	5349.91	110.4	15650.2
inflation	78	1.569	1.083	0	4.5
gfcfinvestment	78	300650.91	301120.11	7706.579	1019377.6
tertiaryedu	78	5311.767	5163.712	75.5	14433
unemployedrate	78	6.277	1.885	3.1	10.4
tradeopen	78	.952	.447	.388	1.813

4. Methodology

To investigate the relationship between innovation and growth a longitudinal study at the country level will be performed using a multivariate time series regression. The dataset with the variables mentioned in the previous section will be used. First, the data will be transformed into a log-log model. This is done to make the interpretation of the coefficients clearer and to make the residuals more normally distributed. Some variables had negative values, so they were transformed so that they were all positive, and then they were transformed to log variables. After this, the Hausman test will be performed to determine if a fixed effects or random effects regression is better to use. Fixed or random effects will be used to control for unobserved factors that vary over time or do not vary over time. After the regression is performed there will be a check for multicollinearity by making a correlation matrix and variables that have a value above 0,85 and below -0,85 will be taken out. After that heteroskedasticity will be tested by using xttest3 in Stata and finally serial correlation will be checked by using xtserial in Stata. This is to check if the regression should use robust standard errors. Finally, time dummies are also added to the model to check for yearly effects. After all these checks the final regressions will be performed.

The effect of traditional indicators will be based on the framework of the linear innovation model. This model theorises that innovation starts with basic research and then applied research which transforms into development and produces production and diffusion in the end (Godin, 2006). The production and diffusion of new technologies and the production of high-tech goods will then lead to economic growth. In this research it will be assumed that the new indicators are a form of production and diffusion that partly occurs through innovation that happens without R&D and patents, this will be seen as adopting innovation. As a larger part of innovation in CEE countries happens without R&D and patents compared to Western European countries.

The countries will be split into different groups depending on the analysis that will be performed. These are the different country groups:

All countries: All 17 EU countries mentioned at the beginning of the data section.

Western Europe: Austria, Belgium, France, Germany, Luxembourg, Netherlands.

Eastern Europe: Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia.

4.1 First linear model

The first regressions will be used to measure the effects of classic innovation indicators on GDP. The three regressions performed here only differ in the way expenditure on R&D is measured. The first model measures R&D in the total gross expenditure, the second model measures R&D as a percentage of GDP and the third model splits the measurement of R&D between government and business expenditure. The rest of the variables which include more innovation indicators and control variables stay the same for each model. These regressions are performed on all countries and all years are included. The result of the Hausman test indicates that a fixed-effects model should be used instead of a random-effects model. Then checks for heteroskedasticity and serial correlation are performed. These are both present in the regression so robust standard errors will be used. Here below are the regressions that were performed.

Model 1.1:

$$ln(gdp) = \beta_0 + \beta_1 ln(gerd_{it}) + \beta_2 ln(patentapplications_{it}) + \beta_3 ln(patentsgranted_{it}) + \beta_4 ln(rdpersonnel_{it}) + \beta_5 ln(inflation_{it}) + \beta_6 ln(gfcf_{it}) + \beta_7 ln(tertiaryedu_{it}) + \beta_8 ln(umemploymentrate_{it}) + \beta_9 ln(tradeopen_{it}) + u_{it}$$

Model 1.2

$ln(gdp) = \beta_0 + \beta_1 ln(gerdgdp_{it}) + \beta_2 ln(patentapplications_{it}) + \beta_3 ln(patentsgranted_{it}) + \beta_4 ln(rdpersonnel_{it}) + \beta_5 ln(inflation_{it}) + \beta_6 ln(gfcf_{it}) + \beta_7 ln(tertiaryedu_{it}) + \beta_8 ln(umemploymentrate_{it}) + \beta_9 ln(tradeopen_{it}) + u_{it}$

Model 1.3

$ln(gdp) = \beta_0 + \beta_1 ln(berd_{it}) + \beta_2 ln(gbard_{it}) + \beta_3 ln(patentapplications_{it}) + \beta_4 ln(patentsgranted_{it}) + \beta_5 ln(rdpersonnel_{it}) + \beta_6 ln(inflation_{it}) + \beta_7 ln(gfcf_{it}) + \beta_8 ln(tertiaryedu_{it}) + \beta_9 ln(umemploymentrate_{it}) + \beta_{10} ln(tradeopen_{it}) + u_{it}$

4.2 Comparing the differences between traditional indicators across regions

In the second part of this analysis, the same regressions as in the first part will be performed but interaction effects will be added for each variable that interacts with the dummy for Eastern European countries. This is done to see if the coefficients are significantly different between East and West. Also, a following comparison will be performed of the full sample against just the Eastern European sample to check if more significant results can be found as there only are six Western countries in the sample which may give insignificant results.

4.3 The second model

In this section, the effect of new innovation indicators like high-tech import and export will be tested on GDP. In the first model, the import and export of high-tech products and the number of researchers are tested and in the following models, the number of high-tech firms and number of employees in high-tech sectors are separately added. All these models have the same control variables that were used in the previous section. These regressions first will be performed on all the countries to determine if the new innovation indicators are positively correlated with GDP growth. Then interaction effects for each variable will be added and the regressions will be performed again. These interaction effects will show the difference of each variable between the full sample and the CEE sample. Following the results of the Hausman test fixed effects were used and heteroskedasticity and serial correlation were present so robust standard errors were used. These are the models that were used:

Model 2.1:

$ln(gdp) = \beta_0 + \beta_1 ln(hightechexport_{it}) + \beta_2 ln(hightechimport_{it}) + \beta_3 ln(researchers_{it}) + \beta_4 ln(inflation_{it}) + \beta_5 ln(gfcf_{it}) + \beta_6 ln(tertiaryedu_{it}) + \beta_7 ln(umemploymentrate_{it}) + \beta_8 ln(tradeopen_{it}) + u_{it}$

Model 2.2:

$$ln(gdp) = \beta_0 + \beta_1 ln(hightechexport_{it}) + \beta_2 ln(hightechimport_{it}) + \beta_3 ln(enterpisesmedhigh_{it}) + \beta_4 ln(enterpriseshightech_{it}) + \beta_5 ln(researchers_{it}) + \beta_6 ln(inflation_{it}) + \beta_7 ln(gfcf_{it}) + \beta_8 ln(tertiaryedu_{it}) + \beta_9 ln(umemploymentrate_{it}) + \beta_{10} ln(tradeopen_{it}) + u_{it}$$

Model 2.3:

$$ln(gdp) = \beta_0 + \beta_1 ln(hightechexport_{it}) + \beta_2 ln(hightechimport_{it}) + \beta_3 ln(employmedhigh_{it}) + \beta_4 ln(employhightech_{it}) + \beta_5 ln(researchers_{it}) + \beta_6 ln(inflation_{it}) + \beta_7 ln(gfcf_{it}) + \beta_8 ln(tertiaryedu_{it}) + \beta_9 ln(umemploymentrate_{it}) + \beta_{10} ln(tradeopen_{it}) + u_{it}$$

4.4 The final model

In the final models, the indicators with the most significant coefficients of the previous models will be combined. This is done to determine if the traditional or new indicators have a bigger effect on GDP growth and how big the difference between the indicators is. Interaction effects are added to see the differences of each innovation indicator between the full sample and the CEE sample. This will be performed with the same control variables as all previous models. The Hausman test indicates that a fixed effects model is better to use and the test for heteroskedasticity and serial correlation signal that robust standard errors should be used. Here below are the two models that will be used that combine the new and traditional indicators.

Model 3.1

$$ln(gdp) = \beta_0 + \beta_1 ln(gerd_{it}) + \beta_2 ln(patentapplications_{it}) + \beta_3 ln(patentsgranted_{it}) + \beta_4 ln(hightechexport_{it}) + \beta_5 ln(rdpersonnel_{it}) + \beta_6 ln(inflation_{it}) + \beta_7 ln(gfcf_{it}) + \beta_8 ln(tertiaryedu_{it}) + \beta_9 ln(umemploymentrate_{it}) + \beta_{10} ln(tradeopen_{it}) + u_{it}$$

Model 3.2

$$ln(gdp) = \beta_0 + \beta_1 ln(berd_{it}) + \beta_2 ln(gbard_{it}) + \beta_3 ln(patentapplications_{it}) + \beta_4 ln(patentsgranted_{it}) + \beta_5 ln(hightechexport_{it}) + \beta_6 ln(rdpersonnel_{it}) + \beta_7 ln(inflation_{it}) + \beta_8 ln(gfcf_{it}) + \beta_9 ln(tertiaryedu_{it}) + \beta_{10} ln(umemploymentrate_{it}) + \beta_{11} ln(tradeopen_{it}) + u_{it}$$

5. Results

5.1 Traditional innovation indicators

These first regressions give insight into answering the first hypothesis by showing the effect of innovation indicators on GDP. Across the three models, the traditional indicators show a positive and significant relation with GDP. The following models are all log-log models which mean that the dependent variable increase by the percentage in the coefficient if the coefficient increases by 1 per cent. For example, the effect of GERD is the biggest positive factor and has a significance of 1 per cent because this value is significant it means that a 1 per cent increase in GERD increases the GDP by 14,6 per cent. When the R&D is split between business and government the values of the coefficients combined are still similar to the GERD and still significant. Patents also show a positive significant relation with GDP with the value of patent applications being slightly higher than that of patents granted the difference on average is about 0.010. However, it is interesting that the number of R&D personnel has a negative relation with GDP and that the openness of trade also has a similar relation that was unexpected. Overall, the coefficients of these traditional indicators in the model support the first hypothesis that traditional indicators have a positive relation to GDP growth.

In all the results, the country-fixed effects are not displayed because they would take up a lot of space so the full regression results can be found in the appendix.

Table 3: Fixed effects regression of the logarithm of GDP on traditional innovation indicators

	(1.1)	(1.2)	(1.3)
VARIABLES	log_gdp	log_gdp	log_gdp
log_gerd	0.146***		
	(0.046)		
log_gerdgdp		0.011	
		(0.042)	
log_berd			0.079***
			(0.021)
log_gbard			0.079**
			(0.032)
log_patentapplications	0.029*	0.044***	0.032**
	(0.014)	(0.013)	(0.012)
log_patentsgranted	0.023**	0.032***	0.020***
	(0.009)	(0.010)	(0.006)
log_rdpersonnel	-0.180***	-0.096*	-0.190***
	(0.052)	(0.050)	(0.040)
log_inflation	0.005	0.004	0.007
	(0.008)	(0.010)	(0.008)
log_gfcf	0.087	0.123*	0.108**
	(0.050)	(0.067)	(0.049)
log_tertiaryedu	-0.081	-0.100	-0.084
	(0.057)	(0.059)	(0.057)
log_unemployedrate	-0.089***	-0.089***	-0.080***
	(0.021)	(0.023)	(0.017)
log_tradeopen	-0.306***	-0.254***	-0.277***
	(0.049)	(0.056)	(0.055)
Constant	12.081***	11.894***	11.981***
	(0.765)	(1.029)	(0.759)
Observations	220	220	220
R-squared	0.951	0.942	0.956

Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Traditional innovation indicators in different regions

The previous regressions are performed but an interaction term "east" which indicates if a country is Western or Eastern European is added to each variable to showcase the difference between Western and Eastern Europe. The first visible differences are that a lot of the innovation coefficients like GERD and patents are not significant anymore, only GBARD still has a significant correlation. These wildly different results could be the result of the sample of Western Europe only consisting of 6 countries which might be too small to give initial significant results that can be compared. To solve this issue the sample of Eastern Europe was compared to the full sample of 17 countries and not just the 6 Western countries. This has the result that there are 28 countries mentioned at the bottom of the table and this is due to the analysis where the full sample of 17 countries is compared to 11 Eastern European countries so the Eastern European countries are there twice so they can be compared to the full sample. To make sure that none of the variables are counted twice, the interaction effect of a country being in Eastern Europe is done with each variable so that the original values are still of the regression with the 17 countries. The difference is if just the 11 Eastern European countries would have been used and this difference is assumed to be because Western Countries are not in the comparison sample. Here only the interaction effects of the innovation variables are shown and the interaction effects of the control variables can be found in the appendix.

Table 4: Fixed effects regression of the logarithm of GDP on traditional innovation indicators with interaction effects for Eastern Europe

VARIABLES	(1.1) log_gdp	(1.2) log_gdp	(1.3) log_gdp
log_gerd	0.052		
	(0.069)		
east#log_gerd	0.068		
	(0.074)		
log_gerdgdp		-0.037	
		(0.047)	
east#log_gerdgdp		0.063	
		(0.045)	
log_berd			-0.011
			(0.035)
east#log_berd			0.069*
			(0.036)
log_gbard			0.162**

			(0.074)
east#log_gbard			-0.097
			(0.079)
log_patentapplications	-0.010	0.011	0.002
	(0.022)	(0.030)	(0.023)
east#log_patentapplications	0.033	0.022	0.026
	(0.023)	(0.029)	(0.022)
log_patentsgranted	-0.030	-0.042	-0.019
	(0.025)	(0.039)	(0.029)
east#log_patentsgranted	0.051*	0.071	0.039
	(0.029)	(0.043)	(0.031)
log_rdpersonnel	-0.121	-0.054	-0.138
	(0.095)	(0.181)	(0.084)
east#log_rdpersonnel	0.005	0.002	0.021
	(0.111)	(0.183)	(0.095)
log_inflation	-0.002	-0.004	-0.009
	(0.023)	(0.025)	(0.010)
log_gfcf	-0.086	-0.107	-0.121
	(0.109)	(0.115)	(0.105)
log_tertiaryedu	0.034	0.024	0.003
	(0.041)	(0.054)	(0.033)
log_unemployedrate	-0.052	-0.061	-0.036
	(0.034)	(0.039)	(0.022)
log_tradeopen	-0.354***	-0.349***	-0.182***
	(0.098)	(0.107)	(0.045)
Constant	12.673***	12.393***	12.740***
	(0.840)	(1.345)	(0.845)
Observations	220	220	220
R-squared	0.968	0.962	0.972
Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The following results are more in line with the model in section 5.1 by showing significant and similar coefficients. The coefficients for GERD, BERD and GBARD now are significant in their relation to GDP and the values of these are slightly lower for the Eastern European sample being about 0.012 lower on average, however, this difference is insignificant. The other traditional indicators for patents are also significant and show a similar relation and the applications show a slightly lower coefficient for the number of applications but this number is slightly higher for the number of patents granted. But these differences are also insignificant. The other variables have similar coefficients to the first model in 5.1 with the only major difference being that the coefficient for tertiary education has now become significant. The majority of traditional indicators having a lower value for the Eastern European sample compared to the full sample is in line with the second hypothesis but because these differences are insignificant there is no support for the second hypothesis.

Table 5: Fixed effects regression of the logarithm of GDP on traditional innovation indicators with interaction effects for Eastern Europe

VARIABLES	(1.1) log_gdp	(1.2) log_gdp	(1.3) log_gdp
log_gerd	0.137***		
	(0.040)		
east#log_gerd	-0.012		
	(0.049)		
log_gerdgdp		0.026	
		(0.036)	
east#log_gerdgdp		-0.013	
		(0.041)	
log_berd			0.073***
			(0.017)
east#log_berd			-0.008
			(0.025)
log_gbard			0.078**
			(0.030)
east#log_gbard			-0.014
			(0.040)
log_patentapplications	0.032**	0.045***	0.035***
	(0.012)	(0.012)	(0.011)
east#log_patentapplications	-0.011	-0.014	-0.010
	(0.017)	(0.017)	(0.014)
log_patentsgranted	0.018*	0.026**	0.016**
	(0.009)	(0.010)	(0.006)
east#log_patentsgranted	0.007	0.007	0.007
	(0.011)	(0.014)	(0.009)
log_rdpersonnel	-0.194***	-0.125**	-0.202***
	(0.051)	(0.048)	(0.040)
east#log_rdpersonnel	0.066	0.072	0.069
	(0.075)	(0.076)	(0.058)
log_inflation	0.006	0.004	0.008
	(0.007)	(0.008)	(0.007)
log_gfcf	0.065	0.094	0.083*
	(0.049)	(0.061)	(0.049)
log_tertiaryedu	-0.115*	-0.133**	-0.119*
	(0.056)	(0.057)	(0.059)
log_unemployedrate	-0.086***	-0.089***	-0.078***
	(0.021)	(0.022)	(0.017)
log_tradeopen	-0.318***	-0.283***	-0.288***
	(0.040)	(0.045)	(0.044)

Constant	12.141***	11.943***	12.104***
	(0.571)	(0.797)	(0.574)
Observations	362	362	362
R-squared	0.957	0.950	0.961
Number of countries	28	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 New innovation indicators

In this part, the relation between new innovation indicators on GDP is tested and all models in this part show a significant positive relation with exports of high-tech products on GDP. The other new innovation indicators of the number of high-tech enterprises and the number of people employed by high-tech industries and medium high-tech manufacturing also have significant positive relations with GDP. But overall, the GFCF has the highest positive relation in the first two models with coefficients of 0.154 and 0.151 while the high-tech employment has the highest relation in the third model with a value of 0.144. The coefficients of unemployment and trade openness are also significant and similar to the previous models. The positive relation between the new indicators and GDP growth gives support for the third hypothesis that the new indicators are positively related to GDP growth and is accepted.

Table 6: Fixed effects regression of the logarithm of GDP on new innovation indicators

VARIABLES	(2.1) log_gdp	(2.2) log_gdp	(2.3) log_gdp
log_hightechexport	0.088***	0.077***	0.081***
	(0.025)	(0.026)	(0.027)
log_hightechimport	0.030	0.008	0.006
	(0.046)	(0.043)	(0.038)
log_enterprisesmedhigh		0.031	
		(0.035)	
log_enterpriseshightech		0.040*	
		(0.021)	
log_employmedhigh			0.109*
			(0.062)
log_employhightech			0.144***
			(0.042)
log_researchers	-0.062	-0.066	-0.041
	(0.056)	(0.059)	(0.049)
log_inflation	-0.023**	-0.022**	-0.012
	(0.011)	(0.010)	(0.012)
log_gfcf	0.154*	0.151**	0.140*
	(0.076)	(0.071)	(0.068)
log_tertiaryedu	-0.088	-0.075	-0.162**

	(0.060)	(0.064)	(0.059)
log_unemployedrate	-0.072***	-0.073***	-0.037
	(0.023)	(0.021)	(0.023)
log_tradeopen	-0.515***	-0.476***	-0.461***
	(0.099)	(0.105)	(0.094)
Constant	10.386***	10.020***	9.819***
	(0.741)	(0.882)	(0.600)
Observations	221	221	221
R-squared	0.942	0.946	0.950
Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When the regressions are performed using an interaction term for the CEE countries the differences become visible. The only new innovation indicators that remain significant are the high-tech export and the high-tech employment indicators. The interaction term shows that the coefficient for high-tech export is higher for CEE nations by about 0.022 on average which implies that high-tech export has a bigger relationship with GDP in CEE countries however this difference is not significant. The interaction terms for employment in various high-tech sectors show similar results that were previously found for traditional indicators as they have a lower coefficient for the CEE countries which means that they have a lower relationship with GDP in CEE nations, but also these differences are insignificant. In light of these results, the fourth hypothesis is not accepted. While the indicator of high-tech exports does show a higher coefficient for the CEE sample which is in line with the fourth hypothesis this difference is insignificant.

Table 7: Fixed effects regression of the logarithm of GDP on new innovation indicators with interaction effects for Eastern Europe

VARIABLES	(2.1) log_gdp	(2.2) log_gdp	(2.3) log_gdp
log_hightechexport	0.090***	0.078***	0.083***
	(0.022)	(0.022)	(0.024)
east#log_hightechexport	0.032	0.031	0.039
	(0.034)	(0.030)	(0.036)
log_hightechimport	0.017	-0.001	-0.001
	(0.042)	(0.041)	(0.035)
east#log_hightechimport	-0.037	-0.036	-0.035
	(0.056)	(0.054)	(0.052)
log_enterprisesmedhigh		0.043	
		(0.034)	
east#log_enterprisesmedhigh		-0.036	
		(0.048)	
log_enterpriseshightech		0.027	

		(0.018)	
east#log_enterpriseshightech		0.021	
		(0.028)	
log_employmedhigh			0.119*
			(0.059)
east#log_employmedhigh			-0.047
			(0.084)
log_employhightech			0.123***
			(0.039)
east#log_employhigh			-0.034
			(0.059)
log_researchers	-0.077	-0.075	-0.055
	(0.049)	(0.053)	(0.044)
east#log_researchers	0.049	0.050	0.032
	(0.080)	(0.079)	(0.079)
log_inflation	-0.023**	-0.021**	-0.014
	(0.008)	(0.008)	(0.009)
log_gfcf	0.136*	0.134**	0.124*
	(0.070)	(0.064)	(0.063)
log_tertiaryedu	-0.118**	-0.109*	-0.183***
	(0.052)	(0.055)	(0.053)
log_unemployedrate	-0.067***	-0.067***	-0.035
	(0.023)	(0.021)	(0.022)
log_tradeopen	-0.516***	-0.478***	-0.470***
	(0.077)	(0.083)	(0.073)
Constant	10.221***	10.063***	9.806***
	(0.576)	(0.670)	(0.523)
Observations	364	364	364
R-squared	0.951	0.955	0.957
Number of countries	28	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.4 Comparison of traditional and new indicators between CEE and Western countries

This final part will shed light on the main research question by combining traditional and new innovation indicators in a model so a fair comparison can be made between CEE and Western nations. The results show that GERD or BERD and GBARD combined still have the largest significant relationship with GDP, but the coefficients are slightly lower compared to the model with only traditional innovation indicators. The correlation of patents is also still significant and very similar to previous models. The new indicator of high-tech export also is significant, and the relation is about half the size of the effect of GERD which could also explain why the coefficient of the R&D variables was lower as part of the relationship is captured by this variable. Finally, the rest of the significant variables all have similar coefficients to the previous models.

Table 8: Fixed effects regression of the logarithm of GDP on traditional and new innovation indicators with interaction effects for Eastern Europe

	(3.1)	(3.2)
VARIABLES	log_gdp	log_gdp
log_gerd	0.101**	
	(0.038)	
east#log_gerd	-0.027	
	(0.050)	
log_berd		0.053***
		(0.017)
east#log_berd		-0.014
		(0.026)
log_gbard		0.066**
		(0.028)
east#log_gbard		-0.027
		(0.034)
log_patentapplications	0.029***	0.032***
	(0.010)	(0.010)
east#log_patentapplications	-0.009	-0.009
	(0.013)	(0.012)
log_patentsgranted	0.020***	0.019***
	(0.007)	(0.005)
east#log_patentsgranted	0.004	0.004
	(0.009)	(0.008)
log_hightechexport	0.066***	0.057***
	(0.015)	(0.015)
east#log_hightechexport	0.018	0.019
	(0.022)	(0.022)
log_rdpersonnel	-0.153***	-0.162***
	(0.046)	(0.041)
east#log_rdpersonnel	0.070	0.074
	(0.064)	(0.054)
log_inflation	-0.004	-0.002
	(0.007)	(0.007)
log_gfcf	0.081*	0.090*
	(0.044)	(0.045)
log_tertiaryedu	-0.095**	-0.104**
	(0.043)	(0.046)
log_unemployedrate	-0.069***	-0.064***
	(0.018)	(0.016)
log_tradeopen	-0.471***	-0.422***
	(0.060)	(0.060)

Constant	11.094***	11.177***
	(0.498)	(0.541)
Observations	362	362
R-squared	0.964	0.966
Number of countries	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The difference captured by the interaction term shows similar results to the previous tables. Where the traditional indicators show coefficients which are about 0.23 lower for the R&D indicators and again patent applications had a slightly lower coefficient and patents granted a slightly higher coefficient for CEE countries. The new indicator high-tech trade has a similar larger coefficient to previous models and is 0.19 higher for CEE nations. The other variables also show similar variables to previous models and no big differences are apparent. The fact that the traditional indicators in general show lower coefficients for the CEE sample and that the new indicator high-tech exports shows a higher value for CEE countries is in line with the literature that traditional indicators are expected to have a larger coefficient for Western Countries and new indicators a larger coefficient for CEE countries. However, as these differences are insignificant, they give no support for the research question.

6. Conclusion and Discussion

6.1 Conclusion

In this bachelor thesis, the difference in the effect of various traditional and new innovation indicators on GDP growth between CEE and Western countries was researched. This was done because while there is a lot of literature about the effect of innovation on growth these studies all mainly focus on indicators concerning R&D investment and number of patents. Moreover, these indicators perform the best when using them on developed economies which is not strange when considering that these comparable indicators were first created by developed nations in the OECD and the EU. This thesis aimed to make the relationship between these indicators clearer in more developing countries so that a better comparison can be made with developed countries. Previous studies have been done on innovation in developing countries, but several papers also call for using different indicators in developing countries as innovation happens differently there compared to developed countries. These papers state that innovation in developing countries happens less through large R&D investments and patenting but happens more by adopting inventions or innovating by buying new machines. This is an innovation that cannot be measured by R&D or patent statistics. To compare the effect of new and traditional innovation indicators across Western and CEE nations, multiple regressions were performed where interaction effects were added for comparison purposes. These were done to answer multiple hypotheses and the research question.

In the first part of this thesis, the relationship between traditional indicators and GDP is researched to find out if the dataset used for this thesis will find similar results to previous research. Traditional indicators here are variables that measure a form of R&D investment which here are GERD, BERD and GBARD and the number of patent applications or patents that were granted. Regressions were performed on Western and CEE countries and a significant relation was found between traditional innovation indicators and GDP growth confirming that the relation found in previous research is also consistent with this dataset. Following this result, the first hypothesis is accepted that traditional innovation indicators have a positive relationship with GDP growth.

The following part compares the differences in the relation of traditional innovation indicators between Western and CEE countries using an interaction term for CEE countries and it is found that the coefficients of R&D spending are larger for Western nations compared to CEE nations, but this difference is insignificant. The relationship for patent applications is smaller in CEE nations while the indicator patents granted has a slightly larger coefficient, again these differences were also insignificant. This corroborates that traditional innovation indicators are more suited to measure innovation in Western economies when using R&D indicators but because these differences are insignificant the second hypothesis that traditional indicators show a stronger relationship in Western countries compared to CEE countries is not accepted.

The next step in this research is to test the new innovation indicators to determine the relationship they have to GDP. New innovation indicators are variables like high-tech imports or the number of firms in an innovative industry and the number of employees working in these firms. These are characterised as new innovation indicators as they could capture innovation that happens in the absence of R&D and patents. When tested with the full sample the new indicators of high-tech export, employment in high-tech sectors and the number of high-tech enterprises had the most significant positive relations with GDP, but when just the CEE sample was used the only new indicators that remained significant and positive were high-tech exports and employment in high-tech firms. These results showed that new indicators that can also capture innovation that happens without R&D and patents also have a positive significant relationship with GDP growth. This leads to the acceptance of the third hypothesis as most of the new innovation indicators are positively related to growth.

Next, using interaction terms the difference in effects of these new indicators was tested between Western and Eastern Europe and it was found that high-tech exports had a higher coefficient for CEE countries while employment in high-tech firms had similar results to traditional indicators by having a lower coefficient for CEE nations. But both of these differences were insignificant. Only the indicator of high-tech export would be in line with the fourth hypothesis that the new indicator would have a bigger relation in CEE countries, but this hypothesis is dismissed as this difference was not significant.

Finally, the significant indicators from the traditional and new indicator models were combined to determine the relative size of the traditional indicators compared to the new indicator of high-tech exports and if the differences between Western and CEE countries still hold if the indicators are combined in a model. The results show that in the final model, all variables have similar coefficients to previous models with GERD, BERD, GBARD and patent applications being slightly lower for CEE nations while patents granted and high-tech exports were slightly higher. But, in this model, these differences were also insignificant.

This thesis set out to answer the research question:

Do indicators other than R&D and patents show different levels of innovation in CEE countries and does this effect differ from Western European countries?

Using four hypotheses and testing them using fixed-effects regression models these were answered and have led to the answering of the main research question. After evaluating the hypotheses, the conclusion to the research question is that when using new and traditional innovation indicators to compare innovation between CEE nations and Western European countries there are differences between the indicators, but these differences are insignificant. Meaning that there is no significant difference in the effect each innovation indicator has when compared between CEE and Western countries.

6.2 Implications

The main implications of this research are that policymakers in general should also focus on different innovation indicators as it is shown that although no significant difference between regions is found high-tech exports still had a significant relationship with growth. For example, the report by the European Investment Bank mainly says that R&D in CEE nations should increase to risk not falling into the middle-income trap and increase their growth. In this report, it is also mentioned that the highest share of firms that do innovation participate in adopting innovation and there are no suggestions to increase this type of innovation. So, while it is important to focus on R&D and patents to increase GDP and these should still be encouraged, there should be a bigger focus on how to measure innovation in these countries that happens without R&D and patents as the largest share of innovative firms in the CEE still happens by adopting innovation. A focus on how to increase high-tech exports is a starting point for policymakers to increase innovation. However, it would be best if new innovation indicators are created by the OECD, the EU or the local statistics agency that can specifically measure this type of innovation. This would allow for better comparison of innovation across regions.

6.3 Limitations

The main limitation of this research is that it is assumed that high-tech export also includes exports of products that are innovative and created without patents and low or no R&D investment. The issue with this is that there is a possibility that the high-tech exports in a country may not be innovative or come from large R&D investments or patents. If that is the case the effect of innovation that happens without R&D or patents is not found and this research would have been similar if just traditional indicators were used to compare the CEE countries to Western Europe.

The next problem is that the sample of Western Europe only contained six countries and mainly insignificant results were found when performing regressions on these six countries. Due to this a proper comparison that would show the true difference could not be made as the Western European sample had insignificant results. The differences in this paper come from the difference between the full sample and the sample containing only CEE countries. So, the difference in the coefficients that is found is due to the absence of Western European countries but because they are not fully different samples the true difference between these regions could not be found. This means that the differences between these regions are understated and a potential larger difference could have yielded a significant difference between the countries.

The third issue is that there is limited research on using alternative innovation indicators. Most research still uses different types of R&D or patent indicators as a proxy for innovation to measure the effect of innovation on growth. So, while in this thesis a relation has been found between innovation and economic growth using high-tech exports as a proxy, there is not a lot of literature that has performed similar analyses.

The final problem is that this research has low external validity. Because this research is performed on Western and CEE countries and each country has their specific characteristics these results cannot be interpreted that there would be similar effects to countries outside of Europe.

6.4 Recommendations for further research

For further research custom innovation indicators should be created and then a study over multiple years can be performed with indicators that more accurately measure innovation that happens in the absence of R&D and patents. This would solve the issue of this research where there is uncertainty if the new innovation indicators measure innovation that happens in the absence of R&D and patents. This can allow for better comparisons between regions to see which has more innovation.

Furthermore, more developed nations should be added to the dataset so that the sample of Western Nations can give significant results so that the true difference between CEE nations and the West can be found.

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Appendix

Appendix: A

The four income groups the World Bank uses to classify economies around the world. It is calculated by taking the gross national income (GNI) per capita data in U.S. dollars, converted from local currency using the World Bank Atlas method.

Low: GNI per capita $1,085 or lower

lower-middle: GNI per capita between $1,086 and $4,255

upper-middle: GNI per capita between $4,256 and $13,205

high income: GNI per capita $13,205 or higher

Definitions of each NACE category with the numbers at the beginning being the NACE Rev. 2 codes.

High-technology:

(21) Manufacture of basic pharmaceutical products and pharmaceutical preparations;

(26) Manufacture of computer, electronic and optical products

Medium-high-technology:

(20) Manufacture of chemicals and chemical products;

(27 to 30) Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c. ; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment

Knowledge intensive high-technology services:

(59 to 63) Motion picture, video and television programme production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities;

(72) Scientific research and development;

Total Knowledge Intensive Activities (KIA):

(09) Mining support service activities

(19) Manufacture of coke and refined petroleum products

(21) Manufacture of basic pharmaceutical products and pharmaceutical preparations

(26) Manufacture of computer, electronic and optical products

(51) Air transport

(58 to 66) Publishing activities; Motion picture, video and television programme production and pharmaceutical preparations; Programming and broadcasting activities; Telecommunications; Computer programming, consultancy and related activities; Information service activities; Financial service activities, except insurance and pension funding; Insurance, reinsurance and pension funding, except compulsory social security; Activities auxiliary to financial services and insurance activities

(69 to 75) Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing and analysis; Scientific research and development; Advertising and market research; Other professional, scientific and technical activities; Veterinary activities

(78 & 79) Employment activities; Travel agency, tour operator reservation service and related activities

(84 to 86) Public administration and defence; compulsory social security; Education; Human health activities

(90 & 91) Creative, arts and entertainment activities; Libraries, archives, museums and other cultural activities

(94) Activities of membership organisations

(99) Activities of extraterritorial organisations and bodies

Which categories are part of high-technology trade products according to the SICT:

Aerospace

Computers office machines

Electronics- telecommunications

Pharmacy

Scientific instruments

Electrical machinery

Chemistry

Non-electrical machinery

Armament

Appendix: B

Table 3: Fixed effects regression of the logarithm of GDP on traditional innovation indicators

VARIABLES	(1.1) log_gdp	(1.2) log_gdp	(1.3) log_gdp
log_gerd	0.146***		
	(0.046)		
log_gerdgdp		0.011	
		(0.042)	
log_berd			0.079***
			(0.021)
log_gbard			0.079**
			(0.032)
log_patentapplications	0.029*	0.044***	0.032**
	(0.014)	(0.013)	(0.012)
log_patentsgranted	0.023**	0.032***	0.020***
	(0.009)	(0.010)	(0.006)
log_rdpersonnel	-0.180***	-0.096*	-0.190***
	(0.052)	(0.050)	(0.040)
log_inflation	0.005	0.004	0.007
	(0.008)	(0.010)	(0.008)
log_gfcf	0.087	0.123*	0.108**
	(0.050)	(0.067)	(0.049)
log_tertiaryedu	-0.081	-0.100	-0.084
	(0.057)	(0.059)	(0.057)
log_unemployedrate	-0.089***	-0.089***	-0.080***
	(0.021)	(0.023)	(0.017)
log_tradeopen	-0.306***	-0.254***	-0.277***
	(0.049)	(0.056)	(0.055)
2009.year	-0.076***	-0.069***	-0.071***
	(0.015)	(0.021)	(0.016)
2010.year	0.010	0.019	0.013
	(0.013)	(0.015)	(0.011)
2011.year	0.067***	0.081***	0.069***
	(0.015)	(0.016)	(0.013)
2012.year	0.086***	0.103***	0.091***
	(0.021)	(0.023)	(0.019)
2013.year	0.105***	0.122***	0.107***

	(0.023)	(0.024)	(0.022)
2014.year	0.126***	0.147***	0.132***
	(0.029)	(0.030)	(0.026)
2015.year	0.140***	0.167***	0.150***
	(0.028)	(0.029)	(0.024)
2016.year	0.165***	0.181***	0.163***
	(0.033)	(0.036)	(0.029)
2017.year	0.204***	0.224***	0.203***
	(0.033)	(0.037)	(0.031)
2018.year	0.240***	0.266***	0.243***
	(0.040)	(0.044)	(0.037)
2019.year	0.265***	0.298***	0.265***
	(0.045)	(0.050)	(0.043)
2020.year	0.244***	0.279***	0.241***
	(0.050)	(0.053)	(0.047)
Constant	12.081***	11.894***	11.981***
	(0.765)	(1.029)	(0.759)
Observations	220	220	220
R-squared	0.951	0.942	0.956
Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Fixed effects regression of the logarithm of GDP on traditional innovation indicators with interaction effects for Eastern Europe

	(1.1)	(1.2)	(1.3)
VARIABLES	log_gdp	log_gdp	log_gdp
log_gerd	0.052		
	(0.069)		
east#log_gerd	0.068		
	(0.074)		
log_gerdgdp		-0.037	
		(0.047)	
east#log_gerdgdp		0.063	
		(0.045)	
log_berd			-0.011
			(0.035)
east#log_berd			0.069*
			(0.036)
log_gbard			0.162**
			(0.074)
east#log_gbard			-0.097
			(0.079)
log_patentapplications	-0.010	0.011	0.002

	(0.022)	(0.030)	(0.023)
east#log_patentapplications	0.033	0.022	0.026
	(0.023)	(0.029)	(0.022)
log_patentsgranted	-0.030	-0.042	-0.019
	(0.025)	(0.039)	(0.029)
east#log_patentsgranted	0.051*	0.071	0.039
	(0.029)	(0.043)	(0.031)
log_rdpersonnel	-0.121	-0.054	-0.138
	(0.095)	(0.181)	(0.084)
east#log_rdpersonnel	0.005	0.002	0.021
	(0.111)	(0.183)	(0.095)
log_inflation	-0.002	-0.004	-0.009
	(0.023)	(0.025)	(0.010)
east#log_inflation	0.010	0.013	0.019**
	(0.023)	(0.025)	(0.008)
log_gfcf	-0.086	-0.107	-0.121
	(0.109)	(0.115)	(0.105)
east#log_gfcf	0.228*	0.292**	0.273**
	(0.113)	(0.117)	(0.101)
log_tertiaryedu	0.034	0.024	0.003
	(0.041)	(0.054)	(0.033)
east#log_tertiaryedu	-0.257***	-0.242*	-0.258***
	(0.086)	(0.122)	(0.080)
log_unemployedrate	-0.052	-0.061	-0.036
	(0.034)	(0.039)	(0.022)
east#log_unemployedrate	0.008	0.029	0.002
	(0.035)	(0.041)	(0.023)
log_tradeopen	-0.354***	-0.349***	-0.182***
	(0.098)	(0.107)	(0.045)
east#log_tradeopen	0.033	0.047	-0.078
	(0.096)	(0.112)	(0.048)
2009.year	-0.093***	-0.095***	-0.083***
	(0.012)	(0.015)	(0.012)
2010.year	0.004	0.005	0.005
	(0.013)	(0.014)	(0.012)
2011.year	0.073***	0.080***	0.071***
	(0.014)	(0.016)	(0.012)
2012.year	0.097***	0.106***	0.097***
	(0.019)	(0.022)	(0.017)
2013.year	0.119***	0.128***	0.118***
	(0.024)	(0.026)	(0.022)
2014.year	0.143***	0.155***	0.149***
	(0.029)	(0.031)	(0.024)
2015.year	0.170***	0.187***	0.178***
	(0.029)	(0.032)	(0.024)
2016.year	0.206***	0.219***	0.209***
	(0.034)	(0.039)	(0.028)

2017.year	0.258***	0.275***	0.260***
	(0.035)	(0.042)	(0.030)
2018.year	0.301***	0.324***	0.308***
	(0.040)	(0.048)	(0.035)
2019.year	0.333***	0.360***	0.341***
	(0.047)	(0.056)	(0.042)
2020.year	0.301***	0.326***	0.307***
	(0.053)	(0.061)	(0.046)
Constant	12.673***	12.393***	12.740***
	(0.840)	(1.345)	(0.845)
Observations	220	220	220
R-squared	0.968	0.962	0.972
Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Fixed effects regression of the logarithm of GDP on traditional innovation indicators with interaction effects for Eastern Europe

VARIABLES	(1.1) log_gdp	(1.2) log_gdp	(1.3) log_gdp
log_gerd	0.137***		
	(0.040)		
east#log_gerd	-0.012		
	(0.049)		
log_gerdgdp		0.026	
		(0.036)	
east#log_gerdgdp		-0.013	
		(0.041)	
log_berd			0.073***
			(0.017)
east#log_berd			-0.008
			(0.025)
log_gbard			0.078**
			(0.030)
east#log_gbard			-0.014
			(0.040)
log_patentapplications	0.032**	0.045***	0.035***
	(0.012)	(0.012)	(0.011)
east#log_patentapplications	-0.011	-0.014	-0.010
	(0.017)	(0.017)	(0.014)
log_patentsgranted	0.018*	0.026**	0.016**
	(0.009)	(0.010)	(0.006)
east#log_patentsgranted	0.007	0.007	0.007
	(0.011)	(0.014)	(0.009)

log_rdpersonnel	-0.194***	-0.125**	-0.202***
	(0.051)	(0.048)	(0.040)
east#log_rdpersonnel	0.066	0.072	0.069
	(0.075)	(0.076)	(0.058)
log_inflation	0.006	0.004	0.008
	(0.007)	(0.008)	(0.007)
east#log_inflation	0.001	0.004	0.000
	(0.007)	(0.008)	(0.008)
log_gfcf	0.065	0.094	0.083*
	(0.049)	(0.061)	(0.049)
east#log_gfcf	0.080	0.094	0.075
	(0.062)	(0.075)	(0.056)
log_tertiaryedu	-0.115*	-0.133**	-0.119*
	(0.056)	(0.057)	(0.059)
east#log_tertiaryedu	-0.070	-0.050	-0.079
	(0.081)	(0.089)	(0.085)
log_unemployedrate	-0.086***	-0.089***	-0.078***
	(0.021)	(0.022)	(0.017)
east#log_unemployedrate	0.024	0.037	0.020
	(0.021)	(0.023)	(0.020)
log_tradeopen	-0.318***	-0.283***	-0.288***
	(0.040)	(0.045)	(0.044)
east#log_tradeopen	0.014	0.005	0.022
	(0.051)	(0.056)	(0.054)
2009.year	-0.082***	-0.081***	-0.076***
	(0.011)	(0.015)	(0.011)
2010.year	0.012	0.019	0.016
	(0.011)	(0.012)	(0.010)
2011.year	0.075***	0.088***	0.079***
	(0.013)	(0.013)	(0.011)
2012.year	0.096***	0.113***	0.102***
	(0.017)	(0.019)	(0.016)
2013.year	0.118***	0.134***	0.120***
	(0.019)	(0.020)	(0.018)
2014.year	0.141***	0.160***	0.148***
	(0.022)	(0.023)	(0.020)
2015.year	0.158***	0.183***	0.168***
	(0.021)	(0.022)	(0.019)
2016.year	0.189***	0.204***	0.187***
	(0.025)	(0.028)	(0.022)
2017.year	0.234***	0.254***	0.234***
	(0.025)	(0.028)	(0.024)
2018.year	0.276***	0.302***	0.279***
	(0.029)	(0.033)	(0.028)
2019.year	0.304***	0.337***	0.305***
	(0.033)	(0.037)	(0.032)
2020.year	0.285***	0.317***	0.282***

	(0.036)	(0.040)	(0.035)
Constant	12.141***	11.943***	12.104***
	(0.571)	(0.797)	(0.574)
Observations	362	362	362
R-squared	0.957	0.950	0.961
Number of countries	28	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Fixed effects regression of the logarithm of GDP on new innovation indicators

VARIABLES	(2.1) log_gdp	(2.2) log_gdp	(2.3) log_gdp
log_hightechexport	0.088***	0.077***	0.081***
	(0.025)	(0.026)	(0.027)
log_hightechimport	0.030	0.008	0.006
	(0.046)	(0.043)	(0.038)
log_enterprisesmedhigh		0.031	
		(0.035)	
log_enterpriseshightech		0.040*	
		(0.021)	
log_employmedhigh			0.109*
			(0.062)
log_employhightech			0.144***
			(0.042)
log_researchers	-0.062	-0.066	-0.041
	(0.056)	(0.059)	(0.049)
log_inflation	-0.023**	-0.022**	-0.012
	(0.011)	(0.010)	(0.012)
log_gfcf	0.154*	0.151**	0.140*
	(0.076)	(0.071)	(0.068)
log_tertiaryedu	-0.088	-0.075	-0.162**
	(0.060)	(0.064)	(0.059)
log_unemployedrate	-0.072***	-0.073***	-0.037
	(0.023)	(0.021)	(0.023)
log_tradeopen	-0.515***	-0.476***	-0.461***
	(0.099)	(0.105)	(0.094)
2009.year	-0.122***	-0.124***	-0.104***
	(0.028)	(0.029)	(0.028)
2010.year	-0.014	-0.022	0.000
	(0.026)	(0.025)	(0.025)
2011.year	0.074***	0.063***	0.081***
	(0.019)	(0.017)	(0.018)
2012.year	0.099***	0.087***	0.106***

	(0.023)	(0.022)	(0.023)
2013.year	0.098***	0.084***	0.108***
	(0.027)	(0.026)	(0.025)
2014.year	0.100***	0.084**	0.116***
	(0.032)	(0.031)	(0.029)
2015.year	0.109***	0.095***	0.128***
	(0.033)	(0.031)	(0.029)
2016.year	0.125***	0.109***	0.140***
	(0.039)	(0.037)	(0.033)
2017.year	0.196***	0.177***	0.205***
	(0.040)	(0.040)	(0.034)
2018.year	0.236***	0.215***	0.244***
	(0.047)	(0.048)	(0.038)
2019.year	0.249***	0.228***	0.258***
	(0.053)	(0.053)	(0.041)
2020.year	0.216***	0.196***	0.217***
	(0.058)	(0.058)	(0.046)
Constant	10.386***	10.020***	9.819***
	(0.741)	(0.882)	(0.600)
Observations	221	221	221
R-squared	0.942	0.946	0.950
Number of countries	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Fixed effects regression of the logarithm of GDP on new innovation indicators with interaction effects for Eastern Europe

VARIABLES	(2.1) log_gdp	(2.2) log_gdp	(2.3) log_gdp
log_hightechexport	0.090***	0.078***	0.083***
	(0.022)	(0.022)	(0.024)
east#log_hightechexport	0.032	0.031	0.039
	(0.034)	(0.030)	(0.036)
log_hightechimport	0.017	-0.001	-0.001
	(0.042)	(0.041)	(0.035)
east#log_hightechimport	-0.037	-0.036	-0.035
	(0.056)	(0.054)	(0.052)
log_enterprisesmedhigh		0.043	
		(0.034)	
east#log_enterprisesmedhigh		-0.036	
		(0.048)	
log_enterpriseshightech		0.027	
		(0.018)	
east#log_enterpriseshightech		0.021	

		(0.028)	
log_employmedhigh			0.119*
			(0.059)
east#log_employmedhigh			-0.047
			(0.084)
log_employhigh			0.123***
			(0.039)
east#log_employhigh			-0.034
			(0.059)
log_researchers	-0.077	-0.075	-0.055
	(0.049)	(0.053)	(0.044)
east#log_researchers	0.049	0.050	0.032
	(0.080)	(0.079)	(0.079)
log_inflation	-0.023**	-0.021**	-0.014
	(0.008)	(0.008)	(0.009)
east#log_inflation	0.005	0.006	0.003
	(0.009)	(0.009)	(0.010)
log_gfcf	0.136*	0.134**	0.124*
	(0.070)	(0.064)	(0.063)
east#log_gfcf	0.105	0.088	0.098
	(0.081)	(0.073)	(0.073)
log_tertiaryedu	-0.118**	-0.109*	-0.183***
	(0.052)	(0.055)	(0.053)
east#log_tertiaryedu	-0.029	-0.077	-0.020
	(0.089)	(0.094)	(0.086)
log_unemployedrate	-0.067***	-0.067***	-0.035
	(0.023)	(0.021)	(0.022)
east#log_unemployedrate	0.036	0.032	0.017
	(0.023)	(0.022)	(0.023)
log_tradeopen	-0.516***	-0.478***	-0.470***
	(0.077)	(0.083)	(0.073)
east#log_tradeopen	-0.005	0.021	-0.005
	(0.068)	(0.081)	(0.070)
2009.year	-0.130***	-0.131***	-0.113***
	(0.019)	(0.021)	(0.020)
2010.year	-0.018	-0.025	-0.003
	(0.019)	(0.019)	(0.020)
2011.year	0.075***	0.066***	0.083***
	(0.015)	(0.014)	(0.015)
2012.year	0.105***	0.094***	0.113***
	(0.018)	(0.017)	(0.018)
2013.year	0.103***	0.094***	0.113***
	(0.021)	(0.021)	(0.021)
2014.year	0.109***	0.099***	0.123***
	(0.024)	(0.024)	(0.024)
2015.year	0.120***	0.112***	0.135***
	(0.025)	(0.024)	(0.024)

2016.year	0.141***	0.132***	0.152***
	(0.029)	(0.028)	(0.026)
2017.year	0.218***	0.205***	0.223***
	(0.030)	(0.030)	(0.027)
2018.year	0.262***	0.248***	0.266***
	(0.034)	(0.035)	(0.030)
2019.year	0.280***	0.267***	0.286***
	(0.039)	(0.040)	(0.033)
2020.year	0.245***	0.235***	0.245***
	(0.042)	(0.042)	(0.036)
Constant	10.221***	10.063***	9.806***
	(0.576)	(0.670)	(0.523)
Observations	364	364	364
R-squared	0.951	0.955	0.957
Number of countries	28	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Fixed effects regression of the logarithm of GDP on traditional and new innovation indicators with interaction effects for Eastern Europe

	(3.1)	(3.2)
VARIABLES	log_gdp	log_gdp
log_gerd	0.101**	
	(0.038)	
east#log_gerd	-0.027	
	(0.050)	
log_berd		0.053***
		(0.017)
east#log_berd		-0.014
		(0.026)
log_gbard		0.066**
		(0.028)
east#log_gbard		-0.027
		(0.034)
log_patentapplications	0.029***	0.032***
	(0.010)	(0.010)
east#log_patentapplications	-0.009	-0.009
	(0.013)	(0.012)
log_patentsgranted	0.020***	0.019***
	(0.007)	(0.005)
east#log_patentsgranted	0.004	0.004
	(0.009)	(0.008)
log_hightechexport	0.066***	0.057***
	(0.015)	(0.015)

east#log_hightechexport	0.018	0.019
	(0.022)	(0.022)
log_rdpersonnel	-0.153***	-0.162***
	(0.046)	(0.041)
east#log_rdpersonnel	0.070	0.074
	(0.064)	(0.054)
log_inflation	-0.004	-0.002
	(0.007)	(0.007)
east#log_inflation	0.002	0.002
	(0.007)	(0.008)
log_gfcf	0.081*	0.090*
	(0.044)	(0.045)
east#log_gfcf	0.087	0.084
	(0.057)	(0.054)
log_tertiaryedu	-0.095**	-0.104**
	(0.043)	(0.046)
east#log_tertiaryedu	-0.067	-0.071
	(0.073)	(0.079)
log_unemployedrate	-0.069***	-0.064***
	(0.018)	(0.016)
east#log_unemployedrate	0.032	0.028
	(0.021)	(0.020)
log_tradeopen	-0.471***	-0.422***
	(0.060)	(0.060)
east#log_tradeopen	0.011	0.003
	(0.066)	(0.067)
2009.year	-0.118***	-0.110***
	(0.012)	(0.013)
2010.year	-0.017	-0.012
	(0.011)	(0.011)
2011.year	0.061***	0.065***
	(0.010)	(0.009)
2012.year	0.083***	0.088***
	(0.013)	(0.013)
2013.year	0.092***	0.096***
	(0.015)	(0.015)
2014.year	0.104***	0.113***
	(0.017)	(0.016)
2015.year	0.113***	0.126***
	(0.017)	(0.016)
2016.year	0.138***	0.143***
	(0.020)	(0.019)
2017.year	0.195***	0.199***
	(0.021)	(0.021)
2018.year	0.237***	0.244***
	(0.025)	(0.025)
2019.year	0.258***	0.265***

	(0.030)	(0.030)
2020.year	0.226***	0.231***
	(0.032)	(0.032)
Constant	11.094***	11.177***
	(0.498)	(0.541)
Observations	362	362
R-squared	0.964	0.966
Number of countries	28	28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1