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Master Thesis MSc. Industrial Dynamics and Strategy

THE INFLUENCE OF TECHNICAL INNOVATION ON AGRICULTURAL PRODUCTIVITY

An Empirical Analysis of Determinants in Eastern Europe

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Abstract

The transformative opportunity for agricultural processes in the 21st century is immense. Its industrialisation with ever-larger fields for crops, machinery and excessive use of agrochemicals has salinized, eroded and depleted the soil. Now, technical innovation measured in inventive local activity indicates solutions and scientific trends. Still, national and regional science and technology supply is needed to lift domestic possibilities onto a level that allows the execution for innovation. Per definition, Precision Agriculture Technology can make also small fields effectively useable for crops with calculated and adapted variable rate application and internet-based decision support. It bears the potential for the countries of Eastern Europe to work cooperatively with the new systems, use the data they gather for further developments and be able to use the freed labour force in other sectors.

Keywords: Agriculture. Precision Agriculture Technology, Green Innovation, Environmental Technology, Productivity, Triple Bottom Line, Sustainability

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List of Abbreviations

CEEC – Central and Eastern European Countries

CCM – Climate Change Mitigation

EU – European Union

EPO – European Patent Office

ICT – Information & Communication Technology

IPC – International Patent Classification

NBER – National Bureau of Economic Research

OECD – Organisation for Economic Co-Operation and Development

PA – Precision agriculture

PAT – Precision agriculture technology

PF – Precision farming

PSF – Planting, Sowing & Fertilising

TFP – Total Factor Productivity

USPTO– United States Patents and Trademark office

VRA – Variable rate application

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1. Introduction

Land that is devoted for agricultural purposes covers a majority of the world's countries surface, which reached production outputs of one trillion US Dollar in the year 2000 – a value that tripled to 3.15 trillion US Dollar in 2015 – and accounts for 99 per cent of calories consumed by humans. Agricultural activities have strong impacts on the environment while also employing large populations – especially in developing countries and economies in transition (Ludena et al., 2007; World Bank, 2019). However, the last six decades have seen land degradation through soil erosion, salinization, depletion of nutrients, and loss of biodiversity (Wright, 2012). In the 20th century, countries managed to cover the needed increase in food by using more land to grow more. During the present century, this conversion will no longer work. Also, the practice of utilising increasing amounts of fertilisers, irrigation water and larger machines is reaching the maximum of what air and soil can withstand as decreasing outputs can already be detected in conventional agriculture (Pretty, 2008). Now, the agricultural production has to change towards a science-based method to cover the upcoming food demands, sticking to the resource-based production techniques and not investing in neither the soil nor the environment to renew and sustain, will cause yields to plummet at some point. Food security can only be achieved with increased yields on the same or even less area (Capalbo & Antle, 2015).

Agriculture is a business of high input demands for relatively insecure outcomes. The production outputs are dependent on environmental and weather conditions. Although agricultural outputs are rising in quantity, economic productivity – better said profitability – is shrinking. This is not a problem of slowing growth but of raising input quantities and prices for fertilisers and pesticides among others (Fuglie, 2018). Price and demand elasticities are high and volatile. Higher regulation and especially increasing environmental standards seem to pose risks to the farmers. Growth in this sector is of great political, economic, ecological and social relevance (Balafoutis et al., 2017; Eberhard & Vollrath, 2018). For these reasons among others, studying the determinants of productivity is key to understanding the dynamics of the current market situation. What are the drivers for the farmers beyond input and output prices? How can input cost be lowered while keeping outputs at least stable? What are the benefits for society in total? Underlying trends such as the need to use given spatial distribution more efficiently or better manage resource to maintain soil fertility are untapped. A common belief seems to be, and the innovative tendencies in other business areas confirm, that searching for the next disruption is the most probable way to success. On the contrary, in agriculture has already seen incremental improvements of products and processes can have large effects on an economy due to the mass market character of the production (Pardey, Alston & Ruttan, 2010).

Without technological change, there is no chance for innovation to yield benefits for neither the economy, the environment or the society. All industries are experiencing change by rapid technological advancements but in comparison to many services and manufacturing companies, the primary sector remains relatively slow in development and implementation due to its spatial heterogeneity and decentralized local sub-systems (Wright, 2012). The interactions of technology and policy, originating in rising social cost and linked with knowledge increased are pushing innovation to become ecologically sustainable (Rennings, 2000). The right composition of investments in capital, assets and knowledge enables an ecosystem for green innovation to flourish (van Leeuwen & Mohnen, 2017).

Even though the literature on agricultural technology is emerging and data collection has become more profound over recent years the different studies are for now mostly working in own limited ecosystems; being either of innovation and business nature or agriculture. Little is, however, known of the links between the spheres and how the ambitions of each one of it could be reached in a region when organized and harnessed correctly. The gap is in connection innovation theory with productivity on an aggregate level that shows the possibilities of harnessing technology and policy for the sustainable development of the agricultural sector – especially in developing countries with more potential for change. The present study is taking the first step in this holistic approach by scrutinising the effects of innovation in agriculture at different breadths of definitions.

A practical example from the private sector shows the scope of agriculture and its importance in life through well balanced and healthy nutrition, making further exploration of the determinants of sustainable productivity necessary. Even stronger holds the change of mentality that is already happening in private firms. Large fertiliser producer YARA filed a patent in 1999 on nitrogen sensing technology applied to on-field machinery to directly reduce fertiliser use. Recently, the same company introduced a holistic farm management software. It is an artificial intelligence supported decision tool which was trained with the data from the sensors of the past decades. Although this might seem cannibalising for a business analyst, the strategy of YARA proves the huge market potential these players see in sustainable agriculture. The influence of smart ecological technology helping farmers reduce pollution and become profitable is beneficial for the environment and society. This practical case sets the scene to examine key drivers of change toward higher productivity on a national level.

Hence, the research question on whether regular, green or Precision Agriculture Technology innovation can be associated with agricultural activities that are more economically productive. An extension to the so-called triple bottom line will be discussed in theory to reflect the sustainability attempt of precision agriculture. The objective of this paper is to empirically delve into the gap in literature most precisely defined by the call for future research examining the dynamic aspects of innovation leading to a higher productive performance per worker in a panel data set (Mohnen & Hall, 2013).

Overall speaking, sustainability as a driver of innovation offers a rare opportunity to improve top-line and the bottom line of productivity. On the bottom line are the cost savings through reduced resource consumption, on the top line new markets might be opening up (Nidumolu, Prahalad & Rangaswami, 2009). Mainly the bottom line effects will be considered in this cross-country panel study. It analyses the economic effects of innovation – green and agricultural technology in particular – while controlling for environmental and social benefits, found that innovation plays an important role in increasing profitability by reducing polluting inputs (Popp, Newell & Jaffe, 2010; Barbieri et al., 2016). Productivity increases are especially important in regions where structures are still under development, to free up the labour force for other sectors and to free up land for environmental purposes, such as forestation or insect-friendly flowering meadows as alternatives for intensively used agricultural monocultures (OECD, 2019b). All these changes need sustainability as their baseline. The Brundtland Commission defined its development as: "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, Khalid, Agnelli & Al-Athel, 1987 p.8) considering economics – hence profit, the environment – hence the planet, and well-being of humans – hence its people combined in triple bottom line of productivity.

The region under scrutiny will be a panel data set of Eastern European countries from 1995 to 2015. These countries still have a very segmented structure of agricultural farming with many regions still working under less the 5ha (van Evert et al., 2017) subsistence conditions whereas the comparable average farm size in Western European countries such as Germany is between 10 and 50 ha (Deutscher Bauernverband, 2019). Sustainable Agriculture and Precision Agriculture Technology innovation do not yet show significant results – most likely caused by the time lag that the patents as innovation measure imply. The results offer a good perspective because inventions are future-oriented. So as the start rising in many of the countries will be able to tackle pollution and replace the productivity drivers of today with another more green and efficient technology tomorrow.

The rest of this thesis will be structured as follows. In chapter two the introduced framework and the principles that bring innovation in association with productivity will be outlined. Chapter three focuses on the data; first giving explanations how the study was designed, and which region and the timeframe was chosen. Afterwards, the econometric methodology leading to a comprehensive estimation model will be outlined. In chapter four, the author presents his results and discusses them. Together with the implications from the model, the limitations and future research prospects are shown before closing the thesis with the conclusion.

2. Theoretical Framework

The ambition of this chapter is to explain from the literature if, why and how innovations, green innovations and those in Precision Agriculture Technology are an important determinant of overall agricultural productivity. This section sets the cornerstones by first connecting the theories of productivity with the literature on innovation – including the influences of technology diffusion, policy and patenting – and transfer it to the agricultural sector. By analysing the concepts of structural change, the analysis narrows down the literature of technology innovation in resource-saving and science-based Sustainable Agriculture. In the following sections of this chapter, a two-step framework will support the overarching research to find out whether and which innovation affects agricultural productivity[1]. The first core analyses will examine the combination of productivity and innovation theory and how it applies to the agricultural sector. The second part – now already based within the theorem of green innovations and the agricultural sector – focuses on the influence of Agricultural Technology innovation on productivity.

2.1 Innovation and Productivity

Two large theories of progress will be combined to a more sustainable design of doing agriculture. One is reflecting the input – innovation – and the other the output – productivity. Together, the two theories will be harnessed to create a concept of sustainability in agriculture consisting of less pollution, less resource consumption, less labour force involved by more smart technologies leading to more profitable output and hence productivity.

2.1.1 Productivity

Before a relationship between innovation and productivity can be derived, the latter has to be framed as a starting point of the analysis. Productivity is the summation of incremental increases towards less resource usage and required labour to generate larger outputs that are exceeding the amount explainable by inputs. Productivity growth, conversely, is the amount that output rises more than the input has risen (Jorgenson & Griliches, 1967). In technical terms, this means that productivity in multi input-output scenarios is an output index like value for example divided by the input efficiency such as labour per capital invested (Mohnen & Hall, 2013). The following passages will develop a dynamic view from the above-defined productivity theory in its classic form towards the potential of increases in it triggered by innovation. As a consequence, it should result in sustainable productivity. This implies that that increased productivity does not only mean higher profits but the so-called triple bottom line approach of economic profitability, ecology and social responsibility (Cohen & Winn, 2007) under the influence of free-market failure and the arising double externality situation.

[1] Appendix B is setting the scene that defines the environment the argumentation will be developed in

Theoretically, the most appropriate way to measure productivity is to consider Total Factor Productivity (Ludena et al., 2007). According to their arguments, it accounts for all relevant input factors such as machines used, labour, land use and fertiliser and can detect changes in them in relation to output when measured on the same level of aggregation The possibility of increasing the output in agriculture is determined by many factors on top of the few mentioned in the previous sentence, so that the first step towards consolidating the profitability margin needs to be reducing the inputs. Only if these are minimised at a fixed production level, it can be increased in later stages. Increasing the productivity in agriculture is beneficial for the farmers –mainly in monetary terms through lower production costs – and the rest of the society in the form of a healthy ecosystem and social benefits. The prices will become lower for all and labour gets freed up from subsistence work in developing countries (FAO, 2019b). In its report, the institution points out the over average price elasticity on the markets for agricultural products making it difficult for small scale farmers to survive with labours intensive and inefficient processes; this holds especially for catching up or developing countries. Eberhardt & Vollrath (2018) also stress the high dependency on the elasticity of the agricultural output related to the labour input for regional structural change. They note that the higher the Total Factor Productivity becomes, the lower is the input of labour needed and the higher rises the real income per capita, even stronger so with lower labour elasticity of agricultural production. This elasticity can also be used to detect structural change by comparing it to the value-added of the sector's products (Herrendorf, Rogerson & Valentinyi, 2013). Measuring productivity in a standardised way is difficult due to the wide range of input factors, the volatile output markets and the structural heterogeneity across continents or even countries. On the farm level, for many years, productivity increases were tried to be accomplished with absolute growth in the area used. Subsequently, investments in machinery were heavy and they grew with the farms' size. Other input factors of use during the growing process such as but not limited to irrigation, fertiliser and pesticides usage had to grow with it (Dogliotti et al., 2014). Often neglected however was the investment into the soil (Barnes, 2002). The named scholar calculated the degradation due to intensive agriculture and calls for a regional study that controls for soil pollution through for example excessive fertiliser usage. It is one of the most important input factors but was left behind in the race for higher productivity growth in the conventional way.

For the moment agriculture is a part of the ecological problem but can at the same time be a part of the solution if productivity is measured more holistically and innovations and new technologies are harnessed well. The following section delivers the first part of the possible solution by explaining this situation from the productivity point of view. The triple bottom line is an approach to work against the externalities that arise from markets where the real prices of products are not adequately reflected due to either flawed pricing mechanisms or information asymmetries between producers and consumers. It consists of measuring productivity in a sustainable way for the profits generated, the people involved, and the planet used. For the profit bottom line, economic and monetary terms of profitability are transformed into the real economic value a certain industry has on the economic environment. It is accompanied by the social bottom line orientated at the well-being of the labour force by accounting for interdependencies not only within a corporation but also towards upstream cooperation. This counts especially towards farmers. The last element of the triage is the environmental bottom line aiming to reduce the ecological footprint of a sector by introducing new ways of production, consumption and focusing on circular approaches of recycling, reusing and upcycling (Brundtland, Khalid, Agnelli & Al-Althel, 1987; Cohen & Winn, 2007). After having set how productivity on its own needs to be seen and measured for the given frame of this study, the next section will elaborate in the same way on innovation. In this way, the reader is aware of which of the many streams of prevalent literature this thesis focusses on before analysing the effect of innovation on productivity in the modern agricultural context.

2.1.2 Innovation

This section continues building the cornerstones for the framework by showing the principles for successful innovation, how patents are being used as a practical tool to measure innovation and to show ways that include innovation being positive for the ecology, society and the agricultural sector. Innovation shows great variation not only between countries but also between industries on mainly three parameters. The first is whether demand is coming from a technology push or a demand-pull. Secondly, appropriability conditions determine the success of knowledge protection and thirdly here are great differences in technological opportunity conditions (Cohen, 2010). In today's globalised and multilaterally connected world, domestic national sources are not as important anymore. Even smaller countries by GDP per capita able to extend or even extend their internal innovative potential to adopt technologies developed outside, adapt them to the local requirements and strengthen structural changes domestically to provide a better infrastructure for ongoing innovation (Keller, 2004). The following will first explain the need to protect intellectual property, technology and process forthcomings with patents and how innovation works in the agricultural context in particular.

2.1.2.1 Measuring Innovation: Patents

Patenting is not only a secure and globally aligned way to protect one's innovation against misappropriations and allows the inventor to reap the profits from it but can provide an objective view of a countries innovative output to be measured ex-post. The history of preventing inventions from being misused and to punish fraud is long. Only since the last decade of the 20th century, patent proponents to protect the intellectual property of innovation came forward and many internationally ratified multilateral agreements were arranged. Inventors within or without organisational conjunctions often face a trade-off between the different forms of intellectual property protection and every one of those comes with different benefits and disadvantages (Granstrand, 2005). Patents are normally more appealing to large corporations to prevent imitation, to block competitors from patenting similar inventions, to prevent lawsuits or to ultimately increase its reputation. Although most of these circumstances also hold for smaller firms, especially the last point motivates even small firms to use patents a lot in spite of the high costs of maintaining them (Block, Fisch, Hahn & Sandner, 2015). Since inventions are not restricted by national boundaries, Griliches (1990) describes the diffusion of special technology inventions as very uneven, but traceable with citation patterns. An argument against patenting is that something can be easily invented around it and albeit incurring high costs does not help to protect against misappropriation of an invention (Cohen, Nelson & Walsh, 2000). Opposite to that, patents can encourage innovation when they strengthen the incentive to the inventor. Nonetheless, patents are not always the optimal choice of intellectual property protection because the rewards for each party need to be achievable before informational imbalance resolves and everyone gets access to the unique features of an invention (Wright,1983). Overall, patents might not be the best proxy because they do not represent knowledge spillovers form local research adequately and tend to overly enunciate local interactions, but they do very well reflect the structural change (Acs, Anselin & Varga, 2002). These characteristics are of importance for the relationship to innovation elaborated in the coming sections.

2.1.2.2 Innovation in the Context of Agricultural Productivity

The criteria for successful innovation in agriculture are different from classic innovation theory. Process innovation plays a larger role than product innovation because even innovation in a machine or sensor results in process improvement of the agricultural activity. Furthermore, the agricultural innovation sphere is allowing more incremental changes in the processes because the radical product innovations are only indirectly linked to it from the downstream technology and machinery suppliers (OECD, 2019b).

Two things are important for the setting of the innovative environment that agriculture needs to strive for in the future. First and foremost, the evolutionary and path-dependent dynamism of innovation and technological change stands out (Galende, 2006). It is a dynamic equilibrium depending on the categories of knowledge the innovation is working with – from articulable to tacit and from simple to complex. Only when the right incentives for knowledge and intellectual property protection, such as patenting schemes are taking into consideration (Wright, 1983) innovation will be supported locally. Secondly, the mentioned – in Appendix B –regulatory mix gives even small companies the chance to become visible against multinational giants as they get the tailored support they need to bring their product to a platform of the right scaling potential. The present technology offers many opportunities for farmers that only with the right legal framework prevent dependencies from data collection corporations, allowing technology such as drones and infrastructure to make feasible use of on-site, smart farm management software (Antle, Capalbo & Houston, 2015).

Appropriability of inventions in agriculture and its use for the players is in the economic debate for a long time already. Although Nordhaus (1969) found in his model on the creation of knowledge proxied by patenting that these indeed have a positive influence on the agricultural output, patented innovations did not influence the productivity itself significantly. This was only partly in line with other literature at the time. Griliche's (1967) example of the hybrid corn has shown exactly this significant positive effect on productivity could be explained by a patented invention. The even more interesting finding of that study was that while being a newly bread seed and not outrageously more expensive than previous products, it has spread more easily and quickly in the already well-developed areas of the United States compared to the poor ones. Renski & Wallace (2012) found that in the rural United States the patenting rate among agricultural entrepreneurs is 30 per cent lower than other areas of the country. More recently, Moser, Ohmstedt and Rhode (2017) have proven by measuring patent activities that the introduction of a certain product allows showing the impact of a specific technology type on national agricultural outputs. Even though intellectual property protection is evenly available across the globe for agriculture-related innovation, its execution is biased towards richer and more developed countries. This is especially the case in the protection of breeding but also in technological forthcomings. The high cost of filing and maintaining a patent deters people or firms with fewer earnings to do so (Pardey, Alston & Ruttan, 2010).

Against the common belief in innovation theory that only radical innovation can make a difference and change for the good, Rennings (2000) strengthens the possibilities of incremental increases in standards and technologies because it can take up to 50 years that major innovation is rolled out in detail and has reached the social bottom line. Especially in the agriculture of the 21st century, this counts more than ever before. Apart from many calls for change, the exact detailed proof from where this change could come from remain open. Mohnen and Hall (2013) argue that in general, all four types of innovation – product, process, organizational and marketing can lead to higher revenues.

Hypothesis 1a:
The agricultural productivity of a country is positively associated with technology innovation

2.1.3 Green Innovation

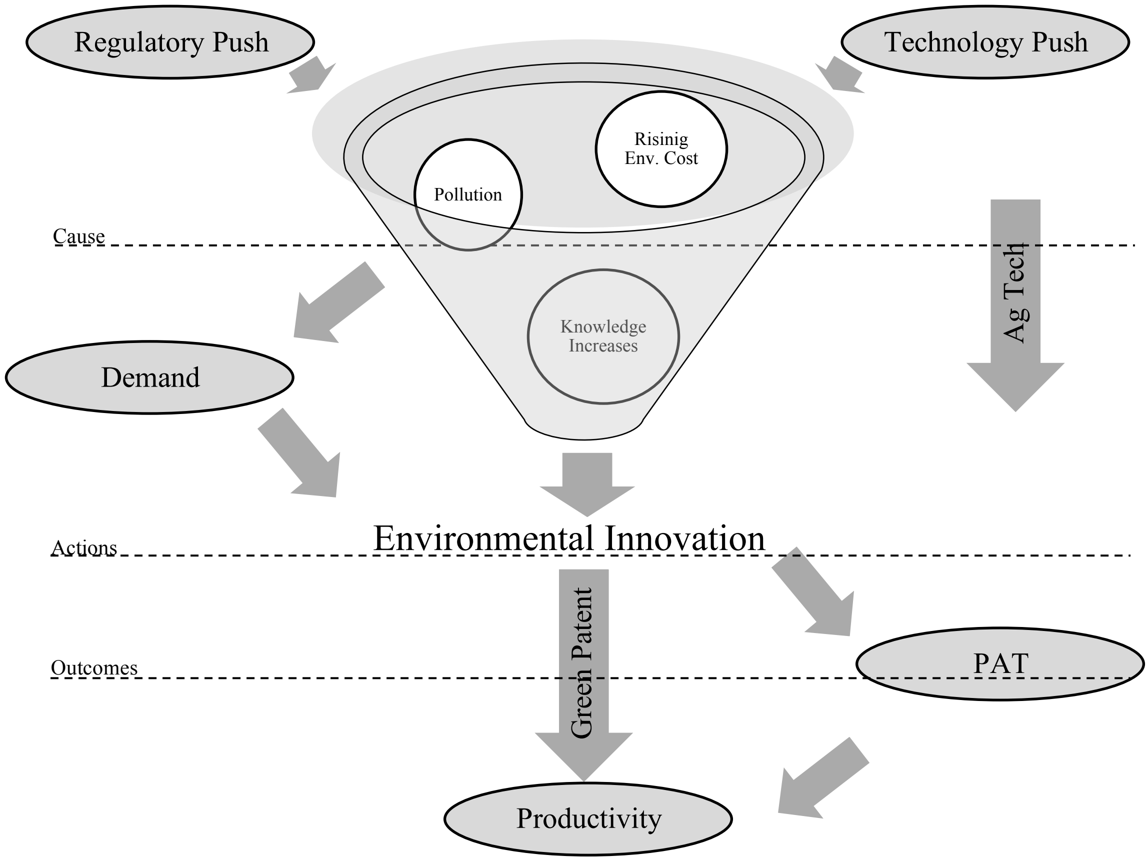
This category of innovation, being located within the sphere of sustainable innovation and entrepreneurship[2], directs its focus especially on the environmental consequences of increased productivity induced by innovation. The term green innovation encompasses two particular outputs of ecological mindful investments in technology research and development. The first is innovation with pollution reduction effects and the second is resource-saving ecological innovation (van Leeuwen & Mohnen, 2017). Innovation stems from knowledge increases in society, recognizable increases in pollution and debates about environmental cost incentives. Rennings (2000) elaborates in his seminal paper that environmental innovation is influenced by three peculiarities. One is the technology push arising from advances in material development and Information and Communication Technology (ICT). The other is a regulatory push into innovation from externally triggered institutional regulations such as the United Nations Sustainable Development Goals (Desai, Kato, Kharas & McArthur, 2018) or the European Commission Horizon 2020 programme (EC, 2019). The last and overarching one is the double externality problem. The negative externalities are in the diffusion phase of innovation caused by ecological harm and failing markets to secure stable compensation for outputs, whereas the positive knowledge spillover for increased innovation (Jaffe, Newell & Stavins, 2005). These to externalities influence the market pull for efficient ways of food production, which is nowadays stronger than it was in the 20th century as education is expanding and alimentary schemes are breaking up[3]. The ecological burdens for change, however, are on a constant rise and can nearly only be offset with increased innovations on resource reduction and lowering the cost of administration. Especially input price changes are an important driver to motivate agricultural firms to reduce pollution, material use, energy consumption and most importantly use process innovation that increases efficiency. Especially this last point enhances productivity on farm level but needs policy support to unfold its fruitful results also on the aggregated level (Horbach, Rammer & Rennings, 2012).

In a recent study, these rather theoretical approaches were studied (Van Leeuwen & Mohnen, 2017). They found that investments in green technology on a national level aim for two outputs; the reduction of pollution and saving of resources. They found statistically significant results for the increase in productivity from resource-saving eco-innovations targeting process issues. Regulation in their case did not influence productivity directly but rather increased the occurrence of innovation activity overall. This proves the case for the many interactions between technology advancements, national-level structural change, the knowledge of the labour force and the overall influence of policy and regulation on it. In Figure 1, this sensitive balance is summarised.

[2] Sustainability is defined in multiple ways in Appendix A, whereas in sustainable entrepreneurship, individuals and firms, "*examine how opportunities to bring into existence future goods and services are discovered, created, and exploited, by whom and with what economic, psychological, social and environmental consequences*" (Cohen & Winn, 2007).

[3] A detailed explanation of the interplay of the externalities is to be found in Appendix B

Figure 1: Determinants of Green Innovation (Author's own development based on Rennings, 2000 and van Leeuwen & Mohnen, 2017)



Agriculture can play a key role in this transition if it also shifts towards strengthening the ecological and social elements in its equation of productivity and align with the goals of sustainability. This means no longer accepting adverse environmental effects as collaterals for higher outputs and implementing technologies that offer accessible and effective solutions that keep the yield steady and use the same amount of resources or less. Lastly, the knowledge of the labour force plays a key role in making food production more sustainable (Pretty, 2008). As a result of these arguments and opportunities, the next hypothesis is formed.

Hypothesis 1b:

The agricultural productivity of a country is positively associated with green technology improvements

2.2 Agricultural Technology Innovation

The idea behind technological forthcomings in agriculture is to move beyond pure economic benefits and also account for the ecology, and social benefits. The triple bottom line of productivity is calculated with developments that work to avoid depleting the capacities of the planet's ecosystem; in other words, to grow crops sustainably in economic and ecologic terms in the long term (Dietz & O'Neill, 2013). The core element of sustainable development is ecologically sensitive innovations, which are needed to overcome environmental burdens to progress (Rennings, 2000). The framework that is built in this thesis partly follows the approach by Rennings (Figure 1) to see sustainable development influenced by pushes of technology advances and friendly and encouraging policies as well as a market pull of e.g. labour costs that need to be lowered. In the face of falling markets with decreasing sales incomes and higher input cost, the intuitive solution for farmers was for decades to intensify the business. With fewer crop species on larger fields supported by chemical fertilisers they saw rising profitability, but it turns out to be only a shorth sighted approach (Dogliotti et al., 2014). Diversification and specialisation of businesses is an element still lacking in the world of agriculture but needed for a reallocation of the efficiently aligned resources to make the development lasting (Samaniego & Sun, 2016). At the bottom of Figure 1, there is productivity as a result of innovation processes. The reason why some industries are ahead and some lack behind lies in the inter-industry variation of innovation performance, which is influenced by technological change caused by market pulls, a limited appropriability on the market and certain technological opportunity conditions (Cohen, 2010).

Across the rather conservative farmers, certain adversity against new techniques of doing business and new technologies can be observed, which weakens the demand-pull (Figure 1). This results from the fact that the direct adopter of environmental technology in many cases does not benefit as much as the society in general does. Hence, the incentives by free-market forces alone are not sufficient to incentivise the development of or change to environmental technologies. Therefore, policy is especially important in this field (Popp, Newell & Jaffe, 2010).

2.2.1 The Concept of Sustainable Agriculture Productivity: Economic, Ecologic and Social Benefits

Development in which green innovation and special technical advancements help resolving the pollution problem of agriculture and make it cleaner and more efficient with the use of technology. Measuring agricultural productivity solely relying on market-oriented indicators such as the input factor-based productivity might easily lead to miscalculations and a bias (McBratney, Whelan, Ancey & Bouma, 2005; Cohen & Winn, 2007). For over 20 years now, farmers – originally in the United States and Western European countries – have started to see their crops and field fruits in a distinguished way of assessing the different demands for care and crop nutrition caused by heterogeneous soil or irrigation conditions (Robert 1993, 2002). These were the first systems of technology-based sustainability in agriculture. Sustainable agricultural systems are reducing the amounts of finite resources consumed or polluting factors spread. Without losing their primary effect of supporting the farmers in reaping optimal yields from their crops, and without injurious effects on the environment the technology is equally accessible to farmers (Pretty, 2008). Productivity is the best way to combine the efficiency of selecting inputs and the profitability of bringing the output to the markets (Syverson, 2011).

This is especially the case for the agricultural sector as the output products can be more easily combined and measured as one than in a multi-product manufacturing company. This of course also holds on the aggregated level this study is working on.

2.2.2. The new way of working in tech-driven agriculture

Agriculture nowadays is a considerably polluting industry, but if the single participants work closely with the innovators[4], crops and fields can be used to work in more unity with the environment and still reap the profits needed for a successful farming business model. The requirements for the industry appear to be set and defined by many scholars already. Cohen and Winn (2007) stress the importance of agricultural productivity growth to cope with a growing world population which is due to reach ten billion inhabitants by 2050. The potential of agriculture for Climate Change Mitigation in the face of this increase in demand is nonetheless high. Technology development focused on-farm practices can make the agricultural industry more sustainable, resource-efficient and produce less pre-market waste. Different and slightly less intense planting techniques can already have visible positive effects on reducing soil erosion and restoring the ground's minerals (Poppe, Wolfert, Verdouw & Renwick, 2015). Moreover, as the same group of scholars continues its argumentation, capturing greenhouse gases in the plants can be a reason to make certain new areas arable. On the savings side, there is even more to it for farmers reaching higher prosperity and resilience the scientists argue. Information and Communication Technology (ICT) implementation might have the largest effects on the traditional business model of farming towards productivity-increasing efficiency. Farmers could become empowered with greater transparency and direct marketing channels towards their customers, cutting our profit consuming traders and increase their economic productivity. Labour saving in agriculture seems to be favourable to free up subsistence labour force into other sectors in developing countries, but there are also tendencies in technology that have debatable effects. In developed countries, it lets farms grow in size, which even stronger spurs consolidation and may reduce small independent farmers. Additionally, farmers become dependent on infrastructure such as broadband internet and positioning technology coverage, which could favour some regions over others (Poppe, Wolfert, Verdouw & Renwick, 2015; Hristoski, Kostoska, Dimovski & Kotevski, 2017).

Generally speaking, it is important to acknowledge the difference in the innovation process in agriculture in comparison to the normally observed secondary or tertiary businesses. The extreme mass-market character of its products of grains, for instance, make incremental process improvements already very valuable and potentially change bringing (Gollin, 2010). The quest for the next disruptive product innovation happens more in the downstream supply businesses that provide for example crop surveillance technology or devices for the application of fertilisers at a variable rate (Kempenaar, 2017).

[4] Rennings (2000) calls for this cooperation in the definition for Eco Innovation (Appendix A)

These observed circumstances support the definition of agriculture as an environment of creative accumulation. It is a sector of process innovation with conservative customers that do not buy directly from every new entrant entrepreneur. This also causes a high cumulativeness of technological advances expressed in gradual advances to tacit process-related best practices (Breschi, Malerba & Orsenigo, 2000). The first part of the second hypotheses derived from it reads as follows.

Hypothesis 2a:
The agricultural productivity of a country is positively associated with innovation in Agriculture Technology

Agricultural technology itself is a wide-spanning term that does not oblige to fulfil all the previously outlined criteria of sustainability. To show that exactly this is possible, the following section takes a closer look at Precision Agriculture Technology, which per its green definition transforms agricultural activity to a more sustainable form of production.

2.2.3. The concept of Precision Agriculture Technology and its application

This compound of techniques and practices aims to raise productivity by securing profitability with higher efficiency and especially protecting the environment. It preserves the natural resources that are the cornerstone of a country's food security and sovereignty. At the same time more secure ways of data usage and privacy policies have to be designed. By providing scientific proof and background knowledge, Robert (1993, 2002) makes the case of understanding a field as a heterogenic compound of crops. An adapted treatment is only possible through high-end technological crop and soil surveillance, which was in its many variations later framed below the still evolving term Precision Agriculture (Figure 1). Today's scholars, for example a group around the Wageningen University researcher Van Evert, define Precision Agriculture as the recording, reacting or guidance techniques that deals with management of spatial and temporal variability of soils and crops to improve economic returns and reduce the environmental impact of farming processes (Van Evert et al., 2017). Precision Agriculture does not only help farmers towards optimising their input-output balance, but also fosters literacy and numeracy through educational programmes and hence supports productivity and modernization indirectly as literacy is strongly correlated with the rate of adoption for technologies in models (Kumar & Mittal, 2000).

Further developing the above concepts, Precision Agriculture Technology (PAT) is a site-specific and data-based method, with which farmers intent to optimize returns of inputs while preserving their human, mechanic and natural resources. It can lower soil and air pollution as well as greenhouse gas emissions through targeted need-orientated inputs (Balafoutis et al., 2017). Precision Agriculture Technology consists of many subforms that comprise all kinds of digital solution provision, crop surveillance and management support including long term predictions from past data to instant consultation from on-site data collection. It is directed towards a more productive, profitable, and sustainable conjunction of systems (van Es & Woodard, 2017). Nowadays, high-speed information and computer technology are reaching people all over the globe. Even the most remote rural areas are spurred by the implementation of high-end ICT and open data exchange. Outcomes are for example field images made by special cameras detecting the irrigation status, satellite images indicating the need for pesticides or sensing to check the chlorophyll, pH, nitrogen and other nutrition levels. The sensors can be applied to satellites, drones, and field or stationary machinery. Once the drones are connected to the mobile internet they can transfer sensor data in real-time from machine-to-machine to analyze metrics like crop growth, soil quality and composition (Janssen et al., 2017). Schimmelpfennig and Eberl (2016) point out the high cost but also the vast potential through the theoretically possible cost-savings from the use of the global positioning system, soil mapping, yield mapping, equipment auto-guidance systems, and variable-rate input application. Only the implementation proves to be difficult still. Altogether, however, Precision Agriculture Technology already contributes to the reduction of ecological harm on agricultural soil and greenhouse gas emissions (Balafoutis et al., 2017; Kempenaar et al., 2017).

Technology has evolved and grown rapidly over the past two decades. It is, for some time already, able to cut overspending on farms (Robert, 2002). More innovative farmers who adopt new technologies perform better in the relation of factor inputs and outcome differences (Karafillis & Papanagiotou, 2011). The use of Precision Agriculture Technology offers farmers a possibility to get ahead of potentially increased costs feared by higher environmental standards[5] before they are implemented and at the same time lower costs through the reduction of costly inputs (Balafoutis et al., 2017). With its capability to better match demand and supply of inputs such as fertiliser or water among others the sector can lower is the environmental footprint of emissions and pollution. The researchers especially strengthen the importance of reducing the resource intensity of planting, sowing and fertilizing with Precision Agriculture technology. Most certainly, there are also downsides to it. A common fear is that increasing use of Precision Agriculture with all the technology attached, costly gear, and digital application might separate regions and foster disintegration instead of the interconnection and equal accessibility of resources and markets it is aiming for. The process is comparable to the social evolution described by Hockerts and Wüstenhagen (2009). The technology generally contributes positively to the sustainable transformation of an industry, because it improves access to products of higher social and environmental quality to a wider part of the market, but the entrance barriers rise, and cost-conscious large players increase pressure on regulations free diffusion ending in high clustering and sector consolidation. The coming paragraph compares current technologies with a small outlook into the future after the last hypothesis is defined.

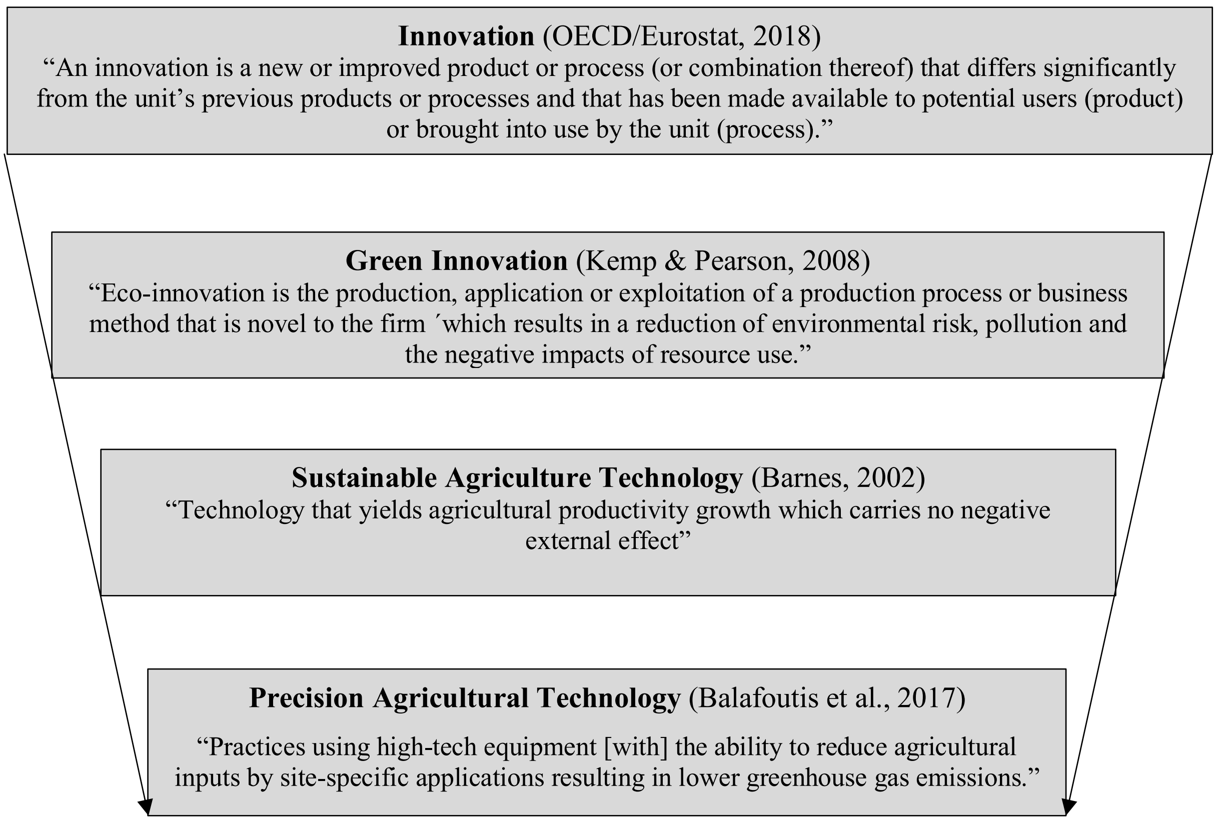
[5] A typical characterisation of Regulatory Push (Figure 1)

Hypothesis 2b:

The agricultural productivity of a country is positively associated with innovation in Precision Agriculture Technology of sowing, planting and fertilizing

With the two derived hypotheses, the framework is set on three levels. The first one is the overarching ambition to explain the if existing, relationship between innovation on the economic productivity in the agricultural sector. Secondly, a narrowing down of the innovation term in the context could be able to show in a more enlightening way, until which specification this relationship can be drawn. These Changing definitions are also part of the third level asking if it is whether and innovative environment in general that influences productivity or if it is rather the specific improvement and development of Agricultural Technology that has an impact as literature shows. Figure 2 gives a final overview of the definitions of innovations used to narrow the research question down onto the 2 hypotheses with their subforms. Altogether, the literature reveals an association of innovation to foster Agricultural Productivity. Combining the special characteristics of innovation in agriculture with productivity theory suggests a positive influence of the former in the latter. A country with more innovative activity, in general, is more likely to show higher agricultural output values.

Figure 2: The Specification of Definitions of Innovation (author's own design)



This chapter has set the theory of productivity and innovation in relation by narrowing down their application from externality induced environmental forthcomings until the effects that Precision Agriculture can yield not only to the farmer in terms of economic productivity but also to society with ecologic and social benefits. Overall, the framework should explain what an environment of favourable conditions should look like to cultivate/promote technological and structural change, public interventions, and growth potential. Therewith it could provide the basis for future research and serve as a decision support tool for policies. The following chapters of this thesis will now translate the principles of above theories into the econometric agricultural context on a country level to see which forms of innovation influence total productivity on a macroeconomic level the most and are therefore interesting for politics and other policymakers to be supported.

3. Data and Methodology

The relationship between innovation and productivity has been studied in length in different contexts but a cross country regional study on technical agricultural innovation influencing the specific productivity of this sector is missing. The gap in the literature of an analysis of the relationship between innovation and productivity in a panel over time (Mohnen & Hall, 2013) will be filled with the econometric analysis of this thesis. After the detailed framing of the theory and setting up two unique hypotheses in the previous chapter, the following one will concentrate on how and with which tools these hypotheses are being tested to answer the research question. Is innovation – in its conventional form, green, or in precision agriculture technology – able to make agricultural activities more productive economically whilst controlling for more elements of the triple bottom line of profitability such as ecologically and socially beneficial activities? The analysis focuses on Central and Eastern Europe; a region with great agricultural potential due to the different climate zones, sparsely populated areas, and high development potential on all three bottom lines (Vehapi & Sabotic, 2015). The proximity to, or membership in, the European Union (EU) and the Organisation of Economic Cooperation and Development (OECD) – can allow the use of financial and structural resources to accomplish the environmental goals of the region (EC, 2019). This chapter is divided into a certain set of subsections. In the data section, the choice of the country and the variables proxying the characteristics leading to more productivity will be analysed. The methodology section then explains the reader the econometric reasoning behind the analysis.

3.1. Data

The core ambition of the previously outlaid hypotheses is to show what the determinants for sustainable and green agricultural innovation – especially in technology-related fields – are and how they lead to increased productivity. The data to achieve this goal was obtained from different sources and aligned and merged manually. Conventional agricultural indicators have been mined at the FAOstat[6] database whereas all indicators related to sustainability, green innovation, ecology in agriculture are from the OECDstat's Green Growth Section[7]. For demographic data, World Bank[8] statistics are added. Special attention was given to data on patents, which will be used as a proxy for innovation as proven to be successful in the literature (for example Griliches, 1990). A comprehensive summary of descriptive statistics is outlined in detail for the relevant variables and their definitions in Appendix C.2. The downloaded data showed very little missing values for most of the variables that should become essential in later modelling. All those with many missing were dropped in the first reshaping process, where variables were brought into alignment on their naming language and equipped with all the same Alpha 3 ISO 3166 country code such as ALB for Albania, a year variable and a unique identification connecting those two (ALB1995 for the values of Albania in 1995). Hereafter, the different sheets were merged on a one to one basis into one core dataset. After a few extra transformations, the dataset was finally fully merged, cleaned and ready to be the groundwork of the analysis. To fulfil the purpose of the hypotheses, it was declared as panel data. It turned out to be a strongly balanced dataset, which linear parameters were collected randomly. Before diving deep into the used variables, the following section will explain the choice of the region.

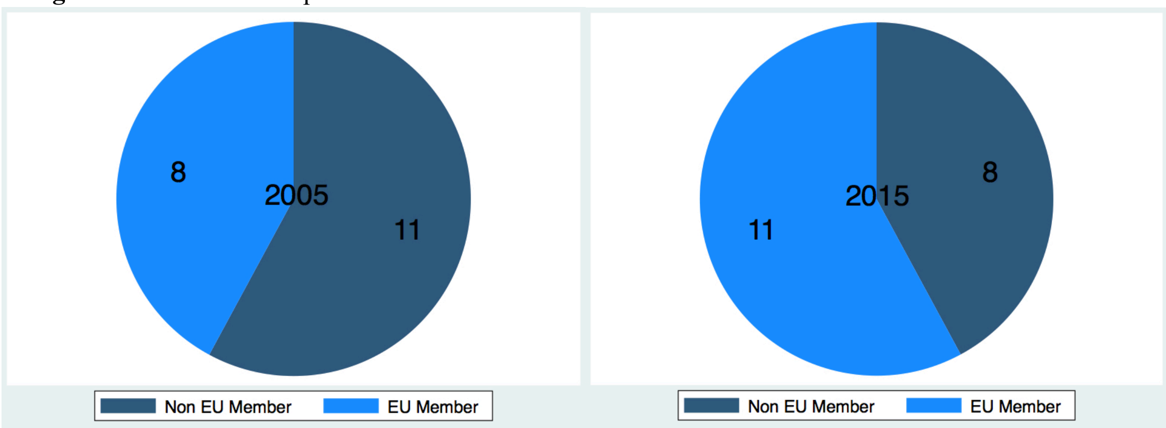
3.1.1 The Region of Eastern Europe and its Importance for the Case

Analysing an area of vast agronomic potential with not much literature yet on the cross-country level has the ambition to point attention towards the importance of long-term sustainable growth. Already now, in an early, less technological phase, investments beyond machinery and chemicals into the development of resource-saving and smart technology can yield returns to both the farmer and society – leapfrogging ahead of industrialised agricultural problems of bagged soil and polluted air. (McBratney, Whelan, Ancey & Bouma, 2005). The area of observation is country-level aggregated data from the Central and Eastern European Countries plus Belarus, the Republic of Moldova and Ukraine making a total of 19 countries; in the following referred to as Eastern Europe. During the observation period from 1995 to 2015, they all underwent transitions from being part of the Union of Soviet Socialist Republics – hereafter called Soviet Union – or the Social Federal Republic of Yugoslavia – hereafter

[6] (FAO, 2019a): http://www.fao.org/faostat/en/#home
[7] (OECD, 2019a): https://stats.oecd.org/Index.aspx?DataSetCode=GREEN_GROWTH#
[8] (World Bank, 2019): https://data.worldbank.org/indicator/NV.AGR.TOTL.CD?end=2016&locations=1W&start=1994&view=chart

called Yugoslavia only – towards approaching the Western European political sphere with its institutions such as the EU and the OECD. These changes are not only of political nature and influence but especially encompass economic circumstances as well as regulations. Regardless of the odds, there are also chances for investment in new technologies and innovation that still need to be recognised and used stronger (Vehapi & Sabotic, 2015). At the beginning of the observation in 1995, none of the 19 countries was a member of the EU and only Czechia was a member of the OECD. Over the years and illustrated in Figure 3, eleven countries have joined the EU in three major waves 2004, 2007 and 2013. For the OECD however, the numbers are smaller until 2015 with only four more countries joining. After

Figure 3: EU Membership of observed Countries 2005 and 2015



the observation period, in 2016 and 2018, Latvia and Lithuania completed the presence of the Baltics in both institutional contexts as they joined Estonia in the OECD.

One of the core reasons to focus on this region in the analysis was its political situation after the breakdown of the socialistic stability and the transition into modern and western style democracies exactly during the period of observation. In the agricultural sector, a solid proxy to show this transition is the EU Membership shown in Figure 3. The Agricultural Sector in Eastern Europe felt this transition especially intensively. Eastern Europe has a very segmented structure of agricultural farming nowadays with many regions' farms still working on less than five hectares family holdings and more in subsistence conditions than targeting the market at full (Vehapi & Sabotic, 2015; van Evert et al., 2017). The comparable average farm size in Western European countries such as Germany is between ten and fifty hectares (Deutscher Bauernverband, 2019). During the time of observation of this study from the mid 1990ies on to 2015, the abolishment of socialistic planned economy practices under the influence of different kinds of seemingly uncoordinated policy approaches and political structures have led to this now observable segregated structure (Tagarakis et al., 2018). Due to the prevalence of two distinct socio-economic conglomerates of peoples in the Soviet Union and Yugoslavia under a political regime different to today's free markets the countries had to undergo a certain calibration from market failure to institutionalised structures. Without doubt, this has brought prosperity and structure to many regions and the integration into the European market allows better exchange of knowledge and products.

However, it is important to keep in mind for policymakers in those countries that innovation policy is not one size fits all. A region with low levels of knowledge-creating institutions, low industrial clustering, and maybe even fragmented in its inter-country interactions should not be treated in the same way than a densely populated coastal area. There has to be differentiation in which tool to use most to make the region develop at the pace of its capabilities in terms of knowledge creation, the endogenous and exogenous flow of company mass and networking (Tödling & Trippl, 2005).

Derived from the literature is the idea that even though agriculture is fragmented and often in subsistence conditions in Eastern Europe there is the chance to reach productivity increases through personal/household and local inventions of precision agriculture technology. Most of the countries in the observation group are not yet able to form national or regional innovation systems (Lundvall & Borrás, 2005). The region, however, manages to bring forward innovation in agriculture by private bodies setting a case against the theory of market failure leading to innovation systems introduced by politics and controlled with polices (REF). After the content and policy-oriented motivation for choosing the dataset is ready, the following sections will elaborate on the variables; especially their structure and usage within the model.

3.1.2 Variables

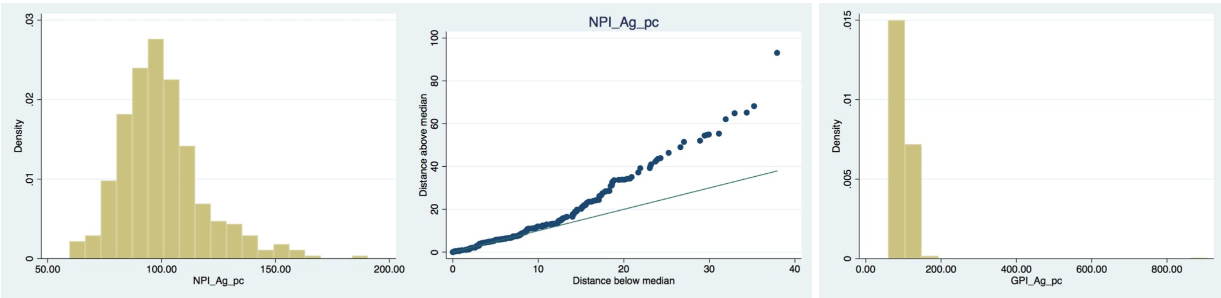
The variables of the dataset were divided into six groups which cover productivity, innovation, demographics and the triple bottom line of economic, ecologic and social productivity necessary to come to conclusive remarks on the sector. This section will show based on which criteria these groups were set up and what indicators available in the dataset they include[9]. Now as the separation of the variables according to the theoretical framework is feasible for modelling the research question of – in short – whether innovation can elevate agricultural activities' productivity. Hence, the next passages translate the thematic grouping into the modelling of dependent, independent and control variables.

The changes in the economic productivity output value as an index around a fixed price level is positively associated with the independent variables of the model. This thesis uses open-source data on the aggregate national level to evaluate this relationship. To answer the research question properly, variables from the FAOstat, the production indices per capita, were sourced without any missing values. It is a Production Index Number[10] on agricultural factors in total. Table 1 shows that the production index is very little correlated to all other variables of the model with no value above 0.26[11]. Its use is oriented on the work of Pardey, Alston and Ruttan (2010) also measuring productivity on and value

[9] The overview about all variables and their descriptive statistics can be found in Appendix C.2. Selected parts will be outlaid in the course of this chapter.
[10] PIN = Index based on fixed level of international dollar of 2004-2006 commodity prices
[11] The detailed overview about all correlations can be found in Appendix G

output per worker index based on fixed values. Figure 4 compares the distribution of the *Agricultural Production Indices* as Net or Gross value, it became clear that the *Net Production Index per capita* was the more evenly distributed and less skewed value of the two; although it still slightly skewed to the right (FAO, 2019). This skewedness might result in a lack of homoskedasticity later on in the modelling, but the concrete methodology in section 3.2 will take on this in more detail. Having the dependent

Figure 4: Histogram and Symmetry of Net Production Index and Histogram of Gross Production Index



variable defined as the *Net Agricultural Production Index per capita* describing the output value in index form, the next sections outline the criteria and develop the suitable variables to complete the model.

3.1.2.2 The Explanatory Variables

The influence of innovation was measured with patent count data. According to the narrowing hypotheses, patent categories span from a broad definition of all patents by the region's residents down to specific Precision Agriculture Technology. To be able to choose an adequate modelling technique outlined in the consecutive sections on methodology, the measurement type of innovation leading to higher productivity is the field that needs the most scrutiny. Against the innovation input Research and Development, it is decided here to use patent count data as the regressor. It represents executed more marketable innovation output assuming productivity in the present scenario happens once the farmers adopt the improved technology. The bare existence of innovation labs would be too far-fetched to translate the results into implications. Notwithstanding, the decision for a main independent variable to describe the amount of innovation input of a country, is one that whole thesis could be written on. Kleinknecht, van Montfort and Brower (2002) compare the different elements very precisely. The choice for patents to proxy innovation in this analysis was taken, because they are relatively objective (Moser, Ohmstedt & Rhode, 2017). Naturally, in patent data, the region of application does not have to be the same with the country of residence of its inventor or applicant as the technology works borderless and its diffusion is especially fast (Keller, 2004). For the present study, this translation, however, would have been out of scope. It does not reduce the value of the study to exclude the diffusion theory and instead concentrate on domestic innovation only. Patenting activities are mostly responsive to policies in the countries of residence of the applicants; foreign regulations appear not to affect inventive activities. Even further, countries still seem to innovate in products that have been patented elsewhere before (Popp, 2006). This means that observing the patent activities in Eastern Europe is indeed a valid insight into the innovative activities of the sector there regardless, whether certain technologies might already exist elsewhere. Moser and her co-authors also prove the importance of patent citations in the agricultural context. They use Hybrid-Corn breeding patents as an example to elaborate that a patent gains value and efficiency in making a certain region more prone to innovation and new, yield generating approaches in agriculture the more it receives citations from new inventions (Moser, Ohmstedt & Rhode, 2017).

The below Table 1 shows the different variables to choose from for the different hypotheses. All of them are defined according to the source at OECDstat. A detailed description of patenting as innovation measure, the different categories, and the OECD database classifications can be found in the Appendix E. The data considers all patents granted to the respective applicants in the country and year. All patents are measured from the USPTO grant database on the date of grant, meaning that the lag between priority filing and final activity of three to five years is already included. Furthermore, it considers the country of residence of an applicant of a patent – meaning the firm or organization this patent is assigned to, not only the inventor herself. The resulting count numbers are divided by the population in million for a comparable cross-country scale.

The broadest definition that applies here is of the total patent count. *Total US-Granted Patents* encompasses all patents granted regardless the industry or sector they belong to. They proxy the overall innovativeness of a country. For this categorisation, no transformation had to be done after the import. The next, more precisely developed patent count towards sustainability-related innovation regardless of the sector are *Environmental Patents* They are categories composed by the OECD following an own algorithm. The OECD manages the collection sorting and storing data from different offices in a more comprehensive way than the single patent offices around could do (OECD, 2009). The applied search strategy by the OECD to collect the patents is a mixture of the classification, keywords in name and abstract and a manual search and selection process resulting in 80 technological fields that *Environmental Patents* comprise; Climate Change mitigation is a strong rising subgroup within the same (Haščič & Migotto, 2015). In the process of further narrowing down the patent search criteria according to the definitions of Innovation in the hypotheses, the sphere will be now entirely in agricultural technology manually gathered from the OECD database. The *Agricultural Technology Patents* count the number of granted patents filed below the category A01 from the International Patent Classification (IPC) rules (WIPO, 2019). This category is not per se entitled towards technical sustainability, but many process-related improvements of the technologies field below this classification can lead to fewer resources consumption and less pollution once adopted on the farms. However, it has to be noted that patent classifications do not allow a total attribution to an industry and a patent can be filed below multiple classification. In total, this classification gives a proper indication of innovation happening in "*agriculture, forestry, animal husbandry, hunting, trapping, fishing*" (OECD, 2009). The narrowest variable is the IPC that is the closest related to the definition of Precision Agriculture Technology defined in Appendix A. Although it is not itself included in the *Environment Patents*, it is the underlying technology that changes agriculture towards smarter and more conscious resource use, which yields higher profitability for the farm and more sustainability for the society. These *Planting, Sowing and Fertilising (PSF) Patents* measure technologies such as the nitrogen nutrient-sensing technology of YARA mentioned before and described in detail in Appendix D.

Table 1: Descriptive Statistics

Variable Name & Description	Variable Definition	Type / Scale	Obs	Mean	Std. Dev.	Min	Max
DEPENDENT *(y)*							
Net Agri Prod. Index per capita	Net Production Index (Number) for agricultural sector	Index number, per capita	399	100	18.58	59.53	190.53
MAIN INDEPENDENT *(x)*							
Total US-Granted Patents	Patents granted at USPTO by Applicant(s)'s country(ies) of residence	Count, Per million	399	1.86	3.52	0	23.31
Agri Patents (US-granted)	"Agriculture; forestry; animal husbandry; hunting; trapping; fishing (A01)" patents granted at USPTO by Applicant(s)'s country(ies) of residence	Count, Per million	399	0.02	0.06	0	0.52
PSF-Agri Patents (US-Granted)	Planting Sowing & Fertilising Patent Granted by USPTO & sorted by Applicant(s)'s country(ies) of residence	Count, Per million	399	0	0.01	0	0.19
Environmental Patents (US-granted)	All environmentally related Patents granted at USPTO by Applicant(s)'s country(ies) of residence	Count, Per million	399	0.28	0.77	0	9.1

3.1.2.3 Control Variables

To estimate the effect of innovation on productivity with validity, the model was designed to incorporate a set of control variables, which simultaneously influence both the regressors and regressand. The controls are representing the four remaining groups of demographics, economic productivity value relations to other industries, environmental productivity and pollution, and social productivity terms[12]. A total correlation of all variables in the present dataset is to be found in Appendix E[13]; a correlation of completely zero for all variables cannot be achieved, but there is also no apparent issue due to multicollinearity. The controls are variables attempting to include all possible time-variant effects affecting the model from the socio-economic environment of farms within their country that are

[12] All bundled in table form in Appendix C.2, which gives an overview of all variables including their definitions and descriptive statistics.
[13] Table 2 in the Estimation development (3.2.1.1) shows the correlation matrix for the core variables of every of those the groups.

expected to influence the adoption of innovation and the realisation of significant savings to reach higher productivity. Gollin and Rogerson (2014) model the interplay of input and output indicators in the agricultural sector theoretically. Accordingly, an agricultural product is made by labour, land and a manufactured intermediating downstream product. This is the basis on which the selection of control variables for the study in this thesis was grounded. Managing the inputs of consumed energy and non-renewable resources carefully while at the same time keeping emissions and resource consumption low are core maxims in their as well as this thesis model. This maxim also holds according to the triple bottom line approach (Cohen & Winn, 2007) and the externality problem (Jaffe, Newell & Stavins, 2005) outlined in the Theoretical Framework.

The first variable cluster controlled for are the polluting and finite input resources used in conventional agriculture and often indicated in literature (McBratney. Whelan, Ancey & Bouma, 2005; van Evert et al., 2017; Eberhardt & Vollrath, 2018). *Nitrogen Fertiliser* – proxying the depletion of soils through chemicals, *Agricultural Energy Consumption* – showing harm through energy-consuming machinery, and *CO2 emissions per capita* or *production-based CO2 intensity* – standing for air pollution - make the three core spheres of influence in conventional agriculture visible. These three spheres are commonly used as controls in country-level studies. This thesis follows van Evert et al. (2017) who label environmental impacts as negative externalities through the emission of greenhouse gases expressed as CO2-equivalents, the loss of biodiversity resulting from the application of pesticides – a variable with not enough observations in the present dataset, and eutrophication of surface waters resulting from leaching of nutrients, expressed as kilograms of leached nutrient fertiliser. The environment, however, is not the only reason to incorporate more than economic profitability determinants. As Barnes (2002) showed in his study on returns and productivity of UK farming, apart from missing investments in keeping the soil fertile, the social aspect of the triple bottom line of productivity is often neglected by practitioners. Only by controlling for measures such as the *Agricultural Employment Ratio*, the components of societal benefit or harm of farming activity on the macroeconomic level can be proxied. The variable for land used under organic agriculture had too many missing variables to be included, therefore the *Land Used for Agriculture* and the *Land Used for Crop* farming serve to capture the land occupation by agriculture. The output variables *Crop Output in Hectares* and *Wheat Production* from the productivity group are deployed as potential compliments to the value-oriented production values in the dependent variable but they show rather high correlation values of around |0.5|. The variable of Crop Output in Area in specific is used to control for the hectares the agricultural production is happening on. Scholars are calling for exactly this rise in productivity per area instead of increasing total outputs only for a change in agriculture towards sustainability (Baldos & Hertel, 2014). The variable Value-Added Ratio Agri shows the percentage of value-added in agriculture to the total value added per capita in each country. From the summary statistics it became obvious that for *Nitrogen Fertiliser*, *Crop Output in Hectares* and *Wheat Production* to function as reasonable control variables, the natural logarithmic form would be to use. Lastly, the block of demographics and the economic circumstances in each country was entered. Eberhardt and Vollrath (2018) found in their model that a country's living standards are determined by agricultural productivity in relation to the growth rate of its population. This urges to control for population indicators to see the changes in productivity in a relative context. This demand is fulfilled with the *Population Density* and the *real GDP per capita* variables. With the variable setup in place, the next large section of methodology will develop the estimation method by shortly probing its general criteria before explicitly finding the models for hypothesis one and hypothesis two.

3.2 Methodology

In its core, the present study harnesses the earlier described dataset to efficiently and conclusively translate the principles of the prevalent theories from literature into the agricultural context on country level. The thesis will furthermore shed light on the question which forms of innovation influence total productivity on a macroeconomic level the most and are therefore interesting for politics and other policymakers to be supported. The following model development is divided into three steps from checking the preconditions to finding the right estimation method to subsequently adapting it to the hypotheses. This section focuses on transforming the well-structured dataset with all required variables into a concrete estimation of associations from innovation to productivity in the region of Eastern Europe to develop a model; a process that takes three steps. The first step was to probe the present data on the correlations. Secondly, the modelling approaches suitable to answer the research question based on the available literature were tested upon the feasibility and transformed into a basic model. Thirdly, this basic model was adjusted to estimate the hypotheses. The first sets the scene for an association of innovation and economic productivity and then endeavours if green innovation is also or even more strongly to associate with a positive influence. The second hypothesis suggests a significant positive relationship between technology innovation in agriculture on the productivity of the industry in Eastern Europe. The data forms a strongly balanced panel, which suffers from neither attrition nor does it miss any variables. By setting the panel it is accounted for internal heterogeneity. It consists of 19 countries and mostly continuous indicators over a period of 21 years. All variables show both within and between variation. The setting as panel data accounts for internal heterogeneity and enables the case for multi-level modelling; in this specific case executed for the different widths of the innovation definitions.

3.2.1. Checking the suitability with the Correlation Matrix

Before the concrete results of the hypothesis come into observation it is important to analyse the outcomes of the correlation matrix in detail. Appendix G shows the table with all variables involved, but Table 2 gives an overview of the core values. Overall, some relatively high correlations lead to the exclusion of certain variables from the regressions. For the relationships with the dependent variable, the values remain constantly low. There are sometimes correlations way over the threshold of |0.6| which might harm the regression and of course, the serial correlation hypothesis when testing the conditions would not hold, but most of these correlations have a very plausible explanation that proves elements from literature. Before giving some example on these, it has to be made clear that the different innovation measures of patenting will not appear in the same regression later on. Therefore, these can be ignored. A very good example that marks the case for this thesis and especially motivated the testing of Hypothesis 1B is that an increase in soil depletion with higher use of nitrogen fertiliser leads to a higher rate of granted green patents per million inhabitants in a country by a positive correlation of 0.66. A second case is around the employment rate in agriculture which is one element of the social bottom line of productivity in this model. It proves the double need for still a lot more innovation in the region of Eastern Europe. The theory suggests a decrease in employment in Agriculture in most cases associated with more technology freeing up labour force for other important sectors. Often, this results in the development of a community. In the high negative correlation of -0.59 between the employment and the production-based CO2 emissions per capita that not only the agriculture intensives with that but also the society industrialises and emits more greenhouse gases. This calls for sustainable technologies solving this double negative externality problem. On the other hand, a reduction in employment lets the GDP per capita rise with a high correlation value of |0.67|. Overall, a time-related tendency becomes apparent in the data. Most indicators are orientated towards the past, analysing what has happened and be done and therefore calling for rather abstract changes only observable ex-post; in other words, exactly, what control variables should be indicating (Wooldridge, 2015). The main independent innovation determinates of patents, however, show orientation to what will be happening soon. This comes due to the definitions and systematics of patent data described in Appendix E.

Table 2: Matrix of correlations for the Pre-Hypothesis Estimation Method Decision with the basis variables

Variables	σ***	(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Net Agri Pr. Ind.	16.47	1.00								
(3) Total Patents*	2.64	0.14	1.00							
(4) Env. Patents*	0.69	0.20	0.70	1.00						
(5) Green Patents*	1.23	0.09	0.26	0.18	1.00					
(6) Pr. Based CO_2**	0.64	0.12	0.35	0.32	0.35	1.00				
(7) Fertiliser**	0.01	0.20	-0.06	-0.02	**0.66**	0.28	1.00			
(8) Agri Empl. Ratio	3.40	-0.05	-0.37	-0.26	-0.26	**-0.59**	-0.08	1.00		
(9) Agricultural Land	4.81	-0.09	-0.27	-0.17	0.22	-0.21	0.34	0.38	1.00	
(10) real GDP**	3432	0.23	**0.60**	0.38	0.42	0.55	0.10	**-0.67**	**-0.43**	1.00

* US granted by applicant at date of grant per million ** per capita ***Within standard deviation

3.2.2 Finding the Right Estimation Method

To predict the influence of different forms of innovation towards productivity the linear variables of the dataset were matched with the suitable regression method; based on the conditions and assumptions, a fixed-effects estimation was adequate. Generally, in multilinear regressions a certain set of six conditions has to hold (Wooldridge, 2015) that will be evaluated in the course of this section; this process is described in detail in Appendix H. First of all, the parameters and the relationships have to be linear, and the size and sourcing of the panel has to be randomly. Both are fulfilled by the present dataset. The third condition is that none of the independent variables should be constant over time to avoid omittance and that there should not be an exact linear relationship among the independent variables is displayed in Table 2 with the within variation and the correlations described in the previous section. The fourth condition is the zero-conditional mean assumption. This encompasses the urge for the correct functional form, no omitted variable bias and no reverse causality. Most importantly, it requires the strict exogeneity of the explanatory variable meaning it should not at all be correlated with the error term $[E(\varepsilon_{it} | x)=0]$. From the information on the variables in their contextual consistency and statistical form, a first regression is set up as baseline to see general ways of influence and test the Gauss Markov assumptions behind the different linear regressions (Kohler & Kreuter, 2009). The basic expression of the fixed effects model used for this pre-estimation regression is shown in equation one.

$$Productivity_{it} = \beta_0 + \beta_1 Patent_{it} + \beta_2 X_{it} + \alpha_i + u_{it} \quad (1)$$

The left-hand side of the equation is the regressand (y_{it}). As per the research question this needs to be a variable from the productivity group. The right-hand side starts with the constant coefficient β_0 before the main regressor – here expressed by a form of patent count representing innovation – multiplied by its coefficient β_1 is added. The other controls are shown by an exemplary term of x_{it} multiplied by its coefficient. Important to observe is the definition of the error term. The composite error in general is $\varepsilon_{it} = \alpha_i + u_{it}$. The model set up of fixed effects relaxes the strict exogeneity assumption of $[E(\varepsilon_{it} | x)=0]$ by splitting up the generic term of unobservable values into the entity specific, but time invariant intercept α_i accounting for the between variation and the time variant error term u_{it} accounting for both the within and between variation. The former represents country fixed effects such as inhabitants' characterisations or size in geographical terms. As these are time invariant, they do not risk or reduce the associative power of the Fixed Effect model. The latter covers idiosyncratic effects such as unobserved economic or social shocks (Nordhaus & Kalbfleisch, 1998).

Before these findings could be set into place, similar variables per definition have been tested and the effect of scale changes on variables was elaborated. For large single values, logarithmic forms make more sense for the interpretability of the results to work with percentile changes instead of absolute ones. In the present study, the natural logarithm was chosen for *Nitrogen Fertiliser per capita* and the real *GDP per capita*[14]. Standardisation is a form to bring each value into relation to its mean and hence on a one on one comparable scale. A regression with standardised values will be used as a robustness test. Squared variables should be used to show if an effect is changing its size over time. This was not

[14] Compare for reference with descriptive statistics in Appendix C.2

needed in the present case. The model, finally chosen is a fixed-effects estimation. Its advantage over the other multilinear regression in panel data is the exploitation of the within the variation of each variable and the relaxed zero conditional mean assumption avoiding omitted variable bias from time-invariant elements of the error term.

3.2.3. Specify the model for the Hypotheses

To make the basic model suitable to estimate the specific hypotheses, certain adjustments and specific evaluation tests ought to be run. These resulted in a sound setup of control variables for all four model regressions and only the explanatory variable changing. The formula (2) shows the Fixed Effects estimation with the chosen control variables included. The explanatory variable is the only one remaining under change per model. The Patent might be replaced with the exact variables from Table 1. Focussing on the set controls, for eco-innovation, the technologies from *Environmental Patents* are set. The social bottom line is represented by the *Agricultural Employment Ratio* whereas the ecological bottom-line control is split into air pollution from *production-based CO2 intensity* and soil pollution by the use of *Nitrogen Fertiliser*. The economic bottom line control is the relative Value Added from the sector. For demographics, the model controls with *Population Density* of a country and the GDP per capita. The results will not be discussed in detail here but Appendix H deals with the outcomes and the development in more detail. Testing showed that different variations, such as the standardisation of the environmental patents due to the outlier year 2013, and the natural logarithms for fertiliser, GDP and production values, needed to be conducted for more consistent results. A special set of Breusch-Pagan Lagrangian Multiplier tests and extended Wald tests is conducted due to the number of entities being smaller than the time frame. They all confirm, on top of the Hausman test, that the Fixed Effect Estimation should be used and is not biased. After the testing, the fixed effects model is still the one of choice. In the following paragraphs now, the adaption to the variable log-levelling and hypothesis wise transformations will be conducted. For hypothesis one the statistical meaningfulness of including controls such as CO2 emissions as either *CO2 Emissions per capita* or *Production-based CO2 emission per capita* needed to be probed; from a theoretical perspective, it would make sense already. Also, it was investigated, if control for amount-based *Crop Output in hectares* adds value in the regressions. According to the coefficients displayed in Appendix I, the variable of *Production-based CO2 emission per capita is included*. As a control for productivity, the *Agricultural Value Added per capita* remains the only one, because of the correlations making the output values unsuitable.

Although the variable of *PSF Agricultural Technology*, counting patents of planting, sowing and fertilising, shows a within variation its observation values show many times zero inventions granted per year and country. This is in line with what was expected from the literature and the situation observable in these countries. The innovation is not as advanced as in the Western European countries or the overall members of the OECD as the tables and graphs in Appendix F show. To substantiate the validity of the fixed effects model, an alternative to the Hausman test, namely the augmented regression or correlated random effects model is run (Jones et al., 2007). Instead of the variables as such, it uses demeaned values. The exact coefficient's results are not as important in this context as is the post estimation Wald test of joint significance. Its null hypothesis is that all explanatory variables are jointly significant. The results of the test suggest rejecting the null hypothesis, which confirms the Fixed Effects estimation because the unobserved heterogeneity would make the Random Effects Model biased.

$$\begin{aligned} \textit{Net Production Index per capita}_{it} &= \beta_0 + \boldsymbol{\beta_1 Patents_{it}} + \beta_2\, \textit{Production CO2 emission per capita}_{it} + \\ &\beta_3 \textit{Agri Energy Consumption}_{it} + \beta_4 \ln(\textit{Nitrogen Fertiliser per capita})_{it} + \beta_5 \textit{Agri Empl. Ratio}_{it} + \\ &\beta_6 \textit{Agricultural Land}_{it} + \beta_7 \textit{Value Added Ratio Agri}_{it} + \beta_8 \textit{Crop Output Area per capita}_{it} + \\ &\beta_9 \textit{Population Density}_{it} + \beta 10 \ln(\textit{real GDP per capita})_{it} + \alpha_i + u_{it} \end{aligned} \quad (2)$$

In conclusion, the different conditions of models are applied to the dataset to find an estimation method that is not only soundly derived from theory but also compliant with the statistical requirements. Appendix H describes this process thoroughly. Among others, the main panel limitation of cross-country dependency was tested and rejected as well as collinearity issues are minor. Due to not being homoscedastic, the regression was run with the robust standard errors to account for the skewedness of its variations. This panel is strongly balanced and hence offers the chance to test the same type of variable in definitions of narrowing breadth represented by the different layers of patents according to the International Patent Classification Rules (WIPO, 2019). In the following chapter, the results from the hypotheses estimations will be outlaid one by one and the robustness checks will be explained before chapter five devotes the attention towards the interpretation of the findings and their implications.

4. Results

The estimation methods chosen to analyse the hypotheses were well adapted and specified to do so on a basic level so that many coefficients show expected signs and sizes where significant. This analysis is executed in a panel dataset of 19 entities (Countries) over 21 years from 1995-2015, which were sourced mainly from FAO, OECD, World Bank and patent databases (FAO, 2019; OECD, 2019; World Bank, 2019; NBER, 2019). It has included 55 variables that have all zero per cent missing observations. The resulting 399 unique observations keep on a steady level on all four models even as the definition of innovation becomes narrower.

4.1. Hypothesis One: Green Innovation Increases Productivity

In general terms, the innovation variable used is a future-oriented measure on how the grant of patents during the years of measurement will have an impact in the future. The other variables, however, were status quo or past-oriented variables because they proxy finite resources to be consumed for efficiency. All results are combined in Table 3 below. The correlation was checked again for this hypothesis-specific variable composition. The correlation table in Appendix I.1 does not show any values raising doubts about the meaningfulness of the model.

Part one of hypothesis one tests the general innovativeness across the region over time by estimating the influence of a general level of inventive activity without any specification on agriculture onto agricultural productivity. This broad definition helps to set the scene and to develop the idea on to the narrower specification later. The results from the fixed effects regression on the first part of hypothesis one (Model (1) – H1A) on whether the *Total US-Granted Patents* of a country as a proxy for its general innovativeness are positively associated with economic productivity but are not significant on the ten per cent significance level holding all other elements constant. The expectation derived from literature was that the agricultural productivity of a country is positively related to the development in technology innovation; this concerns the general innovativeness prevalent in the region proxied by the number of patents. Although the hypothesis itself could not be confirmed with significance, the results of the control variables are jointly significant. Many show also significant results. For example, holding everything else constant, a ten per cent increase in the area devoted to agriculture yields a significant 6.8 higher *Agricultural Net Production Index* value. A ten per cent increase in the *real GDP per capita* increases the *Agricultural Net Production Index*, ceteris paribus, significantly by 0.35[15]. Part two of hypothesis one estimates the relationship of sustainable technology with the productivity index. For this narrower definition towards innovation in the green ecology sphere, the fixed effect estimation with *Total Environmental Patents* (Model (2) – H1B) as explanatory variable shows a positive effect; significant on the five per cent significance level ceteris paribus. Also, many of the control variables show the assumed results and are highly significant. Patents for environmental-related climate mitigation technology can hence be associated with a positive significant effect on economic agricultural productivity. This finding does not only support the framework from the theory that agriculture itself can become part of the solution for reducing pollution and curbing CO2 emissions, but also that there are already measurable actions taken in Eastern Europe. An overview of the results can be found in Model (2) of below Table 3. The control variables of the regressions show very similar results to those in Model (1). According to the correlations described earlier, the utilisation of *Nitrogen Fertiliser* per capita shows a significant on the five per cent level relationship to productivity. A ten per cent increase can increase the *Net Production Index* value by 0.05.

[15] Value estimated by 38.05*log(1.1) = 3.63*log(1.1) = 0. .3456

Table 3: Fixed Effects Regression Results for Hypothesis One and Two
Main regressions on the dependent variable Net Production Index per capita

VARIABLES	(1) – H1A NPI_Ag_pc	(2) – H1B NPI_Ag_pc	(3) – H2A NPI_Ag_pc	(4) – H2B NPI_Ag_pc
Regressor: Innovation				
Total US-Granted Patents	0.219			
	(0.496)			
Environmental Patents US-granted		1.944**		
		(0.919)		
Agricultural Patents (US-granted)			-3.283	
			(8.104)	
PSF-Agri Patents (US-Granted)				18.32
				(18.47)
Control Group I: Ecology				
Production-based CO2 emission per capita	2.655	2.485	2.449	2.517
	(1.778)	(1.829)	(1.751)	(1.772)
Agricultural Energy Consumption per capita	1.546	1.513	1.611*	1.604
	(0.907)	(0.919)	(0.927)	(0.930)
Nat. log. of per capita Nitrogen Fertiliser Application	5.653**	5.476**	5.690**	5.690**
	(2.447)	(2.465)	(2.454)	(2.449)
Control Group II: Social				
Agricultural Employment Ratio	0.00562	0.0138	-0.0171	-0.0171
	(0.417)	(0.418)	(0.416)	(0.417)
Agricultural Land Ratio of total land area	0.685***	0.694***	0.696***	0.697***
	(0.233)	(0.238)	(0.230)	(0.232)
Agricultural Value Added per capita Ratio of total value added	1.818***	1.790***	1.851***	1.844***
	(0.424)	(0.408)	(0.410)	(0.411)
Control Group III: Demography				
Population Density	-2.839***	-2.836***	-2.786***	-2.801***
	(0.816)	(0.810)	(0.793)	(0.797)
real GDP per capita (2010 Int. US-Dollar)	38.05***	37.86***	39.39***	39.11***
	(9.353)	(9.038)	(8.630)	(8.847)
Constant	-66.07	-64.75	-81.88	-78.53
	(139.1)	(135.7)	(131.1)	(133.6)
Observations	399	399	399	399
R-squared (within)	0.599	0.604	0.598	0.598
Number of Countries	19	19	19	19

Robust standard errors in parentheses
The patents are already lagged in the way they were sourced by the OECD (see Appendix E)
*** p<0.01, ** p<0.05, * p<0.1

4.2 Hypothesis Two: Agricultural Innovation not showing significant influence

There cannot yet be significant association on productivity from agricultural innovation and Precision Agriculture Technology proven in Eastern Europe. Again, for this hypothesis, the estimation methods of Fixed Effects and Random effects were compared. This time, however, due to many values being zero – no invention per million inhabitants in a certain country and year – the correlated random-effects model, also called Mundlak estimator, was executed to assure the right model choice (Schunk, 2013;

Wooldridge, 2015). This regression as a test is needed on top of the Hausman test in the decision between Fixed and Random effects, because the within variation could be too low, leading to a violation of the endogeneity conditions of the model as it omits time-invariant variables. The results show that the hypothesis of endogeneity can be rejected and therefore the unobserved heterogeneity does not play a role. The fixed Effects model is still the unbiased estimation model of choice. The correlation was compared and different variable constellations fitting the theory were probed upon their statistical feasibility as done in the previous model as well. The correlation table in Appendix J.1 does – except logically explainable demographic connections between, for example, the size and the Agricultural Land used – not show any correlations above 0.5. This signals that a strong set of variables for the estimation of Hypothesis two was chosen. The best variable choice is derived in Appendix J.2, which illustrates that the same set of control variables as in hypothesis one delivers the most accurate results. Neither the non-logarithmic values nor the inclusion of the highly correlated crop output values was making the results statistically more accurate. The paragraph to come explains in detail the outcomes of the two models on innovation in the agricultural sector and their influence on the productivity of the same.

Part one of hypothesis two (Model (3) – H2A) tests agricultural innovation estimated by the relationship of Agricultural Technology Patents on the Net Production Index. Although the setting is again strong for the results of the control variables proving the unchanged general conditions of the sectoral environment, the main independent variable does not yield significant results on an association of more innovations in the agricultural field to higher productivity in that same sector. The results of the Model (3) in Table 3 investigating the influence of the agricultural innovation bundled in the category A01 (WIPO, 2019) fails to deliver a significant association to the net agricultural productivity in value terms. The coefficients of the control variables of this regression stay mostly coherent with those from hypothesis one and are discussed in section 5.2. One result, however, stands out. Only in this model, the Agricultural Energy Consumption is positively associated with the relationship of innovation to productivity on the ten per cent significance level. Part two of hypothesis two (Model (4) – H2B) focusses on the essence: Precision Agriculture Innovation. The very narrow definition encompasses high technology improvements of proactive and reactive sensing and decision support tools. It is not able to prove a positive association to productivity as assumed from models in the theoretical framework (McBratney, Whelan, Ancey & Bouma, 2005). As an example of the technological speciality in precision agriculture of planting, sowing and fertilising, the sensor of Yara presented, in the beginning, is elaborated on in Appendix D. It is important to note that patents are often filed in multiple classifications at the same time. So, although, this A01C of planting, sowing and fertilising fits perfectly into the core of what most definitions describe as Precision Agriculture stated in the Theoretical

Framework it is not exclusively it[16]. Furthermore, the data shows even more values being zero in this very unique topic of a niche development for countries that lag behind western standards in some parts of its domestic inventive structures. In the regression itself, the coefficients of (4) are nearly unchanged in comparison to regression (3) of the previous, broader definition of this second hypothesis. The regressors do not show significant results most probably due to too little time-related variation.

4.3 Robustness Check

In spite of the thoroughly chosen variables and derived regressions, there was still a need for comparative regressions to confirm with certainty that the results are strong, stable, unbiased and well to interpret. A combined robustness check for both hypotheses was conducted, including four separate tests, namely a reverse causality test, models with all variables in a standardised form, models with squared regressors; altogether displayed in Appendix K.

First and foremost, it was important to confirm with the reverse causality test that only the main independent patent variables determine the productivity indicator and not vice versa. The purpose was to confirm the meaningfulness of the explanatory variables. For a first impression, the literature was searched, but nothing was found on the reversed relationship. Therefore, the Granger Reverse Causality Test was conducted where the causality of y on x is the null hypothesis that was rejected on the ten per cent level.

Secondly, the regressions from the four models were run with standardised values. This check has the ambition to detect irregularities arising from the scales of the distinct variables. Standardisation equals all variables around the same reference and eradicates differences in scales. The values remaining are directly comparable. For overview purposes, the four regressions of this check are inserted below in Table 4. The results of this test confirm the original model in sign and significance in all variables. Thus have, for example, standardised Environmental Patents also a positive significant association on the five per cent significance level ceteris paribus on productivity as they have in the base scenario. Hence, the regression with standardised variables gives proof that the different scales used in the original regressions do not pose a problem on the validity of the coefficients.

[16] McBratney, Whelan, Ancey & Bouma (2005) state that there is not one exact and constant definition of the field possible but a few complementary ones are nevertheless listed in Appendix A.

The third test also works with the same models as the central analysis, but it inserts a squared term for the patent count with the intention to prove the intuitive suggestion of increasing patenting in this particular field of observation along with the overall increases in patents filed around the globe (Kim & Lee, 2015) and especially in the USPTO (Appendix F.3) . Unfortunately, the values do not appear to be significant, failing to prove this expected tendency.

Table 4: Robustness Check Two with standardised variables (Excerpt from Appendix K)

VARIABLES	H1A- STD std_NPI_Ag_pc	H1B- STD std_NPI_Ag_pc	H2A- STD std_NPI_Ag_pc	H2B- STD std_NPI_Ag_pc
Regressor: Innovation				
STD - Total US-Granted Patents	0.0414			
	(0.0941)			
STD - Environmental Patents US-granted		0.0806**		
		(0.0381)		
STD - Agricultural Patents (US-granted)			-0.0110	
			(0.0272)	
STD - PSF-Agri Patents (US-Granted)				0.0103
				(0.0104)
Control Group I: Ecology				
STD - Production-based CO2 emission per capita	0.395	0.370	0.364	0.374
	(0.265)	(0.272)	(0.260)	(0.264)
STD - Agricultural Energy Consumption per capita	0.171	0.168	0.178*	0.178
	(0.100)	(0.102)	(0.103)	(0.103)
STD - Nat. log. of per capita Nitrogen Fertiliser Application	0.329**	0.319**	0.331**	0.331**
	(0.142)	(0.143)	(0.143)	(0.143)
Control Group II: Social				
STD - Agricultural Employment Ratio	0.00357	0.00877	-0.0108	-0.0109
	(0.264)	(0.265)	(0.264)	(0.264)
STD - Agricultural Land Ratio of total land area	0.561***	0.568***	0.570***	0.571***
	(0.191)	(0.195)	(0.188)	(0.190)
Agricultural Value Added per capita Ratio of total value added	0.691***	0.680***	0.704***	0.701***
	(0.161)	(0.155)	(0.156)	(0.156)
Control Group III: Demography				
STD - Population Density	-4.655***	-4.650***	-4.569***	-4.593***
	(1.339)	(1.328)	(1.300)	(1.307)
STD - real GDP per capita (2010 Int. US-Dollar)	1.231***	1.225***	1.274***	1.266***
	(0.303)	(0.292)	(0.279)	(0.286)
STD - Constant	7.42e-09**	7.75e-09**	7.86e-09***	7.85e-09***
	(2.82e-09)	(2.71e-09)	(2.64e-09)	(2.70e-09)
Observations	399	399	399	399
R-squared	0.591	0.604	0.598	0.598
Number of Country_code	19	19	19	19

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

The terminating chapter did in a detailed and separated manner reveal and explain what the regression has brought to the elaboration on innovation as a determinant for agricultural productivity. The coming chapter now will discuss those results in a more aggregated manner and translate these model related insights into implications.

5. Discussion

The ecological mindfulness of investing in new technology that not only supports yields but also attempts to mitigate climate change can have a strong positive impact beyond the borders of the economic productivity of the agricultural sector shown in this study. Probing this relationship more into detail, however, reveals that Eastern Europe has still a lot of potentials to grow into the field of Precision Agriculture Technology.

5.1 Model Related Insights

The results have shed light on three core elements of this study: The positive relationship of climate change mitigation technology improvements on agricultural productivity, the potential of Eastern European countries for a transformative approach to Agriculture and lastly the different time frames that a variable's value can encompass. For most of the chosen agriculture-related control variables, this is a past orientated perspective on how much of a finite resource such as fertiliser, energy or labour was applied or consumed. On the contrary, the innovation determinants proxied by patents work in the opposite direction. The four independent variables show orientation to what will be implemented and commercialised shortly ahead of the point of estimating a certain value[17]. This section discusses them sorted by the hypotheses and the implications from the control variables before it widens again for a joint interpretation and an assessment of opportunities arising from the results.

5.1.2 Harnessing Green Innovation for innovative environmental benefits

This section derives model related insights on the explanatory variable of hypothesis one from its results and discusses its closest implications. The first hypothesis tests whether agricultural productivity can be associated with non-sector specific innovation and green innovation. The latter can be confirmed after its antagonising null hypotheses was rejected on the five per cent significance level. This implies that a country with more inventions for climate change mitigation and environmental technology is significantly associated with higher values of productivity of its agricultural sector; all other elements held constant. This finding comes along also significant productivity increases in conventional agricultural techniques which were held as control variables and will be discussed later (5.1.3). The modelling is based on a sound estimator choice as the side conditions for fixed effects are all fulfilled or accounted for with robust standard errors. The fact that for both specifications there was a positive relationship assumed and that in the broader definition of overall patents this was insignificant but indeed positive for ecological innovations proves many of the claims from the literature on innovation made in Chapter 2. First and foremost, it is confirmed that appropriation is still significantly accomplished by patents, so it is useful for inventors to register a patent in one of the large offices like

[17] In Appendix E the definitions and systematics of patent data that contribute to this orientation are described.

USPTO disproving appropriability doubts (Wright, 1983): It supports the inventor by bringing their products to market and strengthening the informational role of the inventor, for example, to find international investment – including countries not represented among the top industrialised countries (Nagaoka, Motohashi and Goto, 2010). Furthermore, the results enable the author to confirm the technological push is not just happening in the countries but has even gained strength over time and is showing significant productivity increases in net output value. This finding validates the suggested importance of mindful resource consumption and active climate change mitigation supporting not only biodiversity but also the profitability of a volatile and input sensitive sector such as agriculture (Rennings, 2000; Horbach, Rammer & Rennings, 2012). Finally, the results give both insights about sustainable forthcomings being on the agenda already and can be used to further make the point to farmers and other players in the industry that adapting technology is beneficial. The former argument is in line with what Desai, Kato, Kharas and McArthur (2018) found in a study to implement sustainable development goals. They note that new approaches, especially with the new middle class in emerging economies, are contributing its necessary share stronger than in developed countries. This tendency can be proven by a recent study from Eurostat, showing that the Eastern European countries such as the three Baltics, Croatia, Romania, Bulgaria, Slovenia, Czechia, and Hungary, among others, are reaching their 2020 sustainability targets better than their western European Counterparts in the group (Eurostat Press Office, 2019). Therefore, forthcomings in sustainability and environmental innovation are high on the agenda in many countries of Eastern Europe, but still, need more policy support and local infrastructures. In spite of the positive influence that the *Environmental Patents* show on the agricultural economic productivity, it has to be kept in mind that they are only in 3.7 per cent the basis of agricultural science developments – less than the 17.4 per cent of Material Science (Haščič & Migotto, 2015). Therefore, the next section will analyse the findings from the second hypothesis, which encompasses more technical fields of inventions.

5.1.2 Local Precision Agriculture Technology Development not yet in Place

Once environmental technology is developed in Eastern Europe the mindset, knowledge, and scientific background could become available to provide farmers with local solutions for more efficient agricultural solutions. The model related insights from hypothesis two are to be investigated in the following section. This second hypothesis assumes a positive association in which innovative actions in agricultural technology first and Precision Agriculture Technology of planting, sowing, and fertilising, in particular, have a relationship to agricultural productivity values. The literature outlaid in Chapter 2.2 suggests a significant positive effect based on empirical studies from highly developed economies of Western Europe or the United States. The results do not allow rejection of the antagonising null hypothesis even on the ten per cent significance level and are therewith unable to confirm this hypothesis. Nonetheless, the results deliver insights on how these implications are reflected in innovation data from Eastern Europe. Although the infrastructure in Eastern Europe for the application of Precision Agriculture Technology is evolving quickly (van Evert et al., 2017, Tagarakis et al., 2017), the local inventions are not yet able to reflect this trend completely. This is not surprising as one IPC category cannot cover all inventions used for this final application and effect on the field. Domestic Innovation in Eastern Europe is not yet strong enough to build a good database for this ex-post analysis. Especially the time lag to finally obtain measurable productivity increases already described by Griliches (1960) on the hybrid corn seed is confirmed with the results and will be discussed in more detail in section 5.5. Thus, these results do not indicate that the technologies are not used at all. It only indicates a lack of domestic invention. The global adoption and technology diffusion were cut out of the model due to reasons of scope. Overall it can be stated that the local innovation systems behind the conservative sector of agriculture (van Evert et al., 2017) were not developed enough in the years of political change and post-war rebuilding to show significant associations onto productivity.

5.1.4 Insights from Control Variables

Although the explanatory variables could not always deliver the expected results the study benefits from the consistent control variables across the four models. Additionally, this offers the opportunity to infer the implications jointly; they will be discussed in the following section. Many controls are significant for all models and confirm that Eastern Europe is still in a stage where conventional methods are used to strengthen agricultural productivity. This said the room for improvement and national science, technology and innovation systems is urged (Lundvall & Borrás, 2005*). Nitrogen Fertiliser* per capita is the most prominent example for soil depletion in studies on Western European agriculture that have proven that only with increasing input the output can be held stable nowadays (Kempenaar et al., 2017). in the area of this study, it still shows a significant positive increase in holding all other factors constant. Increasing the used amount by ten per cent, for example, increases the total output value per capita by 0.06 points approximately. In the regressions *Nitrogen Fertiliser* per capita has a significant positive influence on the productivity value because, as literature and also practices in Western Europe show, the output increases up to a certain point when the fertility of the soil is exploited. This short-term economic approach, however, does not reflect the harm. The results show overall that conventional agricultural determinants prove their effectiveness in monetary and short-term value terms; holding the respective other determinants constant more use of *Agricultural Land* has a positive effect as has an increase in *real GDP per capita*. On the other hand, side, more *Population Density* leads to less net output value per capita. In the group of social determinants, namely the labour intensity and the use of land for agriculture, show ambivalent results. The former remains insignificant, whereas the latter still shows the intuitive significant relation of more land used leading to higher output. Also, in the setting of sustainable Agriculture derived from the literature, the technological advantage from green patents remain without significant effect. A positive finding is that more CO2 also do not help in raising productivity.

5.2 Model Implications

The model is designed to open a new field of econometric discussion on a region of high agricultural potential but still mostly neglected by current agronomic science – overlooking recent developments of political transition. Due to this motivation, the model is kept rather shallow and wide to open a wide field for further and deeper explorations of the data. This section will now discuss the results in the first stage of abstraction to extrapolate them onto an applied level of actions and benefits for the farmers in an economy. Kempenaar et al. (2017) stress the cost savings from the use of Precision Agriculture Technology. In agriculture, machinery use, and the labour force consume around 30 per cent of the output value. Unfortunately, the significant negative relationship of a higher labour intensity shown in the variable *Agricultural Employment Ratio* with productivity did not turn out in the model, but Kempenaar and his co-authors (2017) were able to estimate a significant 25 per cent decrease in cost by employing variable rate application technology of fertiliser and pesticides brought by sensors such as the N-Sensor of YARA described in Appendix D. Moreover, McBratney et al. (2005) suggested nearly 15 years ago policy measures that might apply now in Eastern Europe for a faster pick up of technologies. Policy and regulation approaches should head for incentives of appropriation of innovation and the acceptance of temporal output variations in such schemes. Additionally, the group suggests focussing more on growing quality and conducts environmental controls. It has to be seen in the context of the politics of the region over the period of observation that was affected by tensions and war so that the focus was different. On top of the above-outlined findings, an additional element of the framework developed in Chapter 2 of this work. There, it has been only touched upon in a shallow manner that adding the social and ecological bottom line to the observation of productivity paired with technical advances in resource-saving and active climate change mitigation can result in more sustainability and higher economic productivity of the agricultural sector. Section 5.3 will describe how the findings from the model can be thought further in combination with theoretical assumptions and insights. This will then also lead to future research suggestions.

There are also scholars, who warn about barriers of adoption towards the technology. Not only might a lack of knowledge or education deter farmers, but it is also difficult for them to compensate for high technological implementation cost with resource savings resulting from the detailed product information obtained through the Precision Agriculture Technology (Schimmelpfennig & Eberl, 2016). The same pair of scholars offered mitigation solutions for this risk by arguing that innovation in agriculture and these specific smart farming technologies, in particular, are introduced sequentially in a one-technology-at-a-time scheme to gradually move forward due to the irreversibility of many steps in agriculture. Additionally, the businesses are highly dependent on output prices, hence big leaps and great investments bear too much risk – even for the most prone farmer imaginable. For the special case of agriculture innovation, Schimmelpfennig and Eberl (2016) can refute the belief of classic innovation literature that incremental improvements cannot deliver substantial forthcomings in technology; here incremental innovations can make a difference. On the opposite side, when widening the spectrum of thought, there are also opportunities arising for the region only loosely proved by this model, but the logical next step to take for policymakers.

5.3 Opportunities arising from the use of Precision Agriculture Technology and Suggestions on how to harness them in an Innovation Policy System

In general terms, there is a tendency that users in developing countries are more prone to utilise data generating and processing technology; the people in these regions see more advantages than disadvantages stemming from big data for their work (Ksethri, 2014). Reconsidering Figure 1 from Chapter 2 shows that the study had covered mainly the right-hand side of the technological push proxied with innovation and assuming a weak pull from the market. Until now in this research, the positive results from the push of advancing technologies is leading to field robotics, smart farming and precise decision support tools. Deeper preconditions are not studied here. By narrowing down the definitions this initial push is leading first to Agricultural Technology (H2A) and then to Precision Agriculture Technology (H2B) graphically displayed on the right-hand side of Figure 1. On the left-hand side, there has been left out the opportunities a rinsing from a stronger regulatory push. In the relative absence of national systematics to increase local innovative ambitions yet (Vehapi & Subotic, 2015; Tagarakis et al., 2018) suggestions towards policymakers can be manifold. Although economists see public policies often from the analytical perspective of market failure, it is important to keep them in a complementary, balanced way instead of substituting each other and be thoroughly analysed beforehand (Edquist, 2011). There are valid critics about governments abilities to take arbitrary decisions on businesses and technological change but without them, the pressing global problems were ignored for the sake of profits end resource exploitation. Therefore, they are justifiable to harness innovative possibilities and technological advantages (Jaffe, Newell & Stavins, 2005). Publicly funded subsidies and aid programmes for farming are well recognized and often applied methods. They, however, have in the past seldom brought the cure they were designed for – either on the national level or institutional one (Lundvall & Borrás, 2005). They unbalance the fragile equilibrium of supply and demand when capping prices on either the top or the bottom as the extreme example of the so-called “butter mountains” of the late 1970ies show (EC, 2015). The European Union should rethink its subsidy programmes as they pose two problems upon Eastern Europe. One is that cheap exports of heavily subsidised products deter local agricultural sectors of those eight countries that are not yet member and have the ambition to become so: The other is – for the countries being member of the EU – often the subsidies by acreage fail to yield support as the large farms are owned by international investors or Western European Cooperatives.

5.4. Future Research

This section will describe the scientific possibilities arising from what the opportunities section before indicating already for practitioners. It works as an outlook of the size of the shoulders this thesis provides for future implication attempts on the topic. This study is only a first small contribution; it is the starting point of a new niche. The thesis focusses on country-level data for policymaking with the ambition to give an overview of regional structural needs, challenges and forthcoming. Nevertheless, it acknowledges the importance of farm-level studies and analysis for policymaking and economic understanding. Future research should, therefore, pick one of the presented countries and study it in depth using innovation surveys and more advanced productivity estimators.

This could extend the current model by more precise estimates to really work with an integrated assessment model that incorporates in more depth the different scientific backgrounds (Nordhaus, 1969) In a two-phase approach, it would include an innovation survey per country on farm level and then use the aggregated results as the productivity total factor productivity dependent variable. An optimal dependent variable for a model taking into consideration the triple bottom line and the two stages would be one that lets the economic, the ecological and the social level be represented from the questionnaire be the regressand for elaborated innovation proxies of both R&D expenditures for innovation input, and multiply lagged patent citations as the output test the same variables as the current study. This being said there are some words to put into evaluating the choice of the patent data as the explanatory variable and other limitations are to consider, which will be laid out in the following last two passages.

5.5 Assessing the Explanatory variable: An Evaluation of Patent Count Data

When using patent data to measure innovation, many scholars, but especially Petra Moser across her publications argue for the use of citations instead of the bare count. The most recent example proving its validity also in the agricultural sphere elaborates on this practice on the example of the patenting of new hybrid corn breeds in the mid of the 20th century in the United States (Moser, Ohmstedt & Rhode, 2017). Against their theoretical line of argumentation, in this thesis, the patent count was used. Mainly three arguments made the determination in favour not to use the citations; two of them are related to availability. Citations show the quality and strength for future inventions and are a proxy of choice for diffusion analysis. Because the latter element was cut out of my statistical analysis through the focus on local inventions and the assumption of domestic execution, the necessity for citations vanishes. Secondly, the citations dataset from the NBER is not as extensive, detailed and versatile as the OECD collection. This makes the citations not groupable as they needed to be for the four specifications according to the theoretical framework developed. Thirdly, the measuring in the available sets ends in

2013[18], so it was extended by the last two years only with a trick of extrapolating the tendency from 2010. Nevertheless, the decline starts already earlier (Figure AC1 in Appendix C), because the measurements of citations happen from the first to the fifth year after the first filing priority date. This would make everything after 2010 not accurate in the main model prediction. Despite the arguments for patenting as a proxy for innovation brought forward in section 2.2.2. they still need a small paragraph here, to show the reader the elements of this intense debate in direct context to the study results. The four patent count variables used in the analysis here, are lagged from the application priority date exactly by the time it took the specific patent from its first appearance on priority date to being granted; a timeframe of normally three to five years. By this time there is not yet the full effect on productivity to measure. Still, the effects of the realisation and especially the commercialisation – in other words, the innovation will be happening from that point onwards. Pardey, Alston & Ruttan (2010), basing their findings also on the diffusion and effects from hybrid corn, estimated that the majority of innovations, namely 28.5 per cent of their sample, leads to its full productive potential only eleven to 20 years after invention date. Keeping this in mind, the analysis if a region like Eastern Europe gains even more importance. The black on white insignificant values of the regressand in three out of four variables might appear as a weak relationship, but its implications for the future show the possibilities and benefits to act ahead of a market pull with a policy-driven technology push (Rennings, 2000). Although the squared value in the robustness check regressions could not significantly prove, patenting has picked up in the last years of the study in the EU that eleven of the sample's countries are a member in at the end (Appendix F.3). This late pick up of own developments can be an explanation for the productivity effects being not yet measurable. Nevertheless, the study is important for the region, to point out ways to strengthen the sector and overcome structural boundaries. For instance, Verhapi & Subotic (2015) describe the disadvantageous ownership structure of farms in Eastern Europe and Serbia in particular. The duo notes that with over 75 per cent of farms being smaller than 5 hectares, the use of conventional machinery is not reasonable, which has hampered productivity increases in the past. Due to the resulting lower productivity, farms could not keep up with cheaper imports and got abandoned, which then lead to an increasing share of income needed to be spent on buying food instead of self-growing activities. This is where Precision Agriculture Technology has the chance to offer solutions in the future. Not only if adopted from foreign technology, but also if local research brings specialized technology for the domestic market forth. Tagarakis el al. (2018) mention the laboratory of *BioSense*[19] aiming to bring tailored and inexpensive technology to the Republic of Serbia. The following two passages will take the results from the models in detail and derive the implications and model-related insights.

[18] A combination of the one available at NBER (until 2006) and one provided by Associate Professor A.S. Bhaskarabhatla of Erasmus School of Economics

[19] Find an overview of the current status of development and services under Research and Development here: https://biosense.rs/?page_id=6597&lang=en

5.6. Limitations and Econometric Uncertainties

After the before discussed choice of the patent data, there remain three limitations to be mentioned. One is, that in addition to the imperfect count data, there is also not net yet a cluster for sustainable precision Agriculture technology in the OECDstat database as there if for Environmental Technology. Secondly, the scope hindered the author to execute a profound two-level estimation including a profound productivity estimation. And thirdly, there was no technology diffusion incorporated.

One of the larger drawbacks is the insignificance for the explanatory variables in the second hypothesis. Only a small number of precision agriculture technology patents per million inhabitants in Eastern European countries were granted. Although this does not hamper the regression technically – the R squared remained high and the Mundlak Estimator confirmed the Fixed Effects – the values might be the reason for the insignificant results showing that the region did not yet pick up own inventions in this field. The attempt to include more of the IP classifications to attempt a replica of the OECD clustering algorithm existent for environmental technology (Appendix E) did not work out on the small scale one could perform it as a single researcher in the limited amount of time available. On top, the unavailability of patent citations in the same detail as the patent count made it insufficient for use as alternative and even more literature proven explanatory variable (Moser, Ohmsted & Rhode, 2017).

Apart from the issue with patent data, the scope leads to several other issues not being developed in their full potential. As indicated in the previous section, the initial intention to work with total factor productivity as a measure for productivity does not work out due to the intense sourcing techniques needed to complete first stage before being able to actually analyse the productivity on the aggregate level as with for example a Malmquist estimation (Ludena el al., 2010). For a real cost-benefit analysis of the added value of Precision Agriculture Technology covering for the not yet available variable in open datasets, the detailed input cost would have been necessary. In the literature on productivity, many model suggestions require preparations exceeding the scope of this work. However, it was attempted to replicate the results of the following approaches in a simplified and minimised way. One exemplary modelling approach was to execute an integrated assessment model as W. Nordhaus (1969) does and include endogenous growth, but this could finally only be reached with the choice of control variables trying to get the closets possible to these results. Calculating the Total Factor Productivity TFP maybe with the Cobb Douglas Formula, if it would have been possible to get hold of data to calculate elasticities. Raymond, Mairesse, Mohnen and Palm (2015) show how the first stage gathering the farm data could have worked out. They use a nonlinear dynamic simultaneous equations models including individual effects and idiosyncratic errors correlated across equations; It estimates these models using two unbalanced panels from three waves of the Community Innovation Survey.

Lastly, innovations were assumed to be implemented, commercialized and adopted primarily in the country of residence of the inventor. Although, this thesis neglects certain elements of the diffusion theory by Keller (2004), the adoption perspective of the farmers, who might be using the patented product in the end, has itself so much to add to the topic that the author decided to leave it out entirely. Technology adoption schemes could not be completely integrated into the data analysis. Therefore, only the local innovations are observed as innovation determinants as if they would be only used these, the use of market common, for example from Western Europe or the United States is left out. Lastly, the area of policy had to be spared from the statistical analysis. Acknowledging the importance of the field it is discussed in the opportunities section only.

6. Conclusion

The empirical analysis suggests that innovation is a probable way to analyse the productivity in the agricultural sector. Two hypotheses were tested to estimate the relationship between an overall positive innovation environment of productivity, and the effect of technology innovation transforming the agricultural sector to become less dependent on input prices while increasing efficiencies. Proxied by patent count, a positive relationship was expected to arise from an overall regional innovativeness (H1A), those inventions targeting ecological objectives through climate change mitigation technology (H1B), those developing new technologies in agriculture (H2A), and most narrowly of the four definitions, those bringing new potential into Precision Agriculture Technology (H2B). Although only the environmental patents show the expected significant positive relationship, all four results together allow a very conclusive assessment of the status of the local innovative environment and status quo in the 19 countries of Central and Eastern Europe in the panel. It has to be considered that in these countries the mechanisation of agriculture has only begun after the breakup of the large socialistic regimes at the beginning of the 1990s. Even since then, a lack of unstructured innovation policy schemes and the lack of structured organisation of the sector have hampered its forthcomings.

From the results in combination with the framework derived in theory, it can be concluded that including environmental problematics into the ambitions to increase productivity can be positively associated with the same. Not only does the regression show significant results, but also there is a strong correlation of the patents count for environmentally-related technology and pollution of soil through fertiliser consumption and air pollution. Additionally, many of the eleven countries of the region that are members of the EU nowadays, will reach their climate mitigation targets for 2020 (EC, 2019). Therefore, it can be said that the first step of the framework – solid mindfulness about the opportunities arising from climate protection through innovation and increasing productivity was fulfilled in the two decades from

1995 on. For the second step – innovations in resource-saving and efficiency increasing agricultural technology from the activities of planting, sowing and fertilising – there is not yet a significant relationship deductible from the analysed data. This might stem from several reasons. The first lies in the future orientation of patents in comparison to the utilisation of finite resource like fertiliser, which shows strong positive influences on productivity throughout all four regressions and is a strong indicator for conventional agriculture. The effect of fertilising a field results in immediately increased output values whereas an invention might take in a positive scenario eleven to 20 years (Pardey, Alston & Ruttan, 2010) or up to 40 years (Rennings, 2000) to unfold its full productive potential. The structural change is anyhow well reflected with patent count (Acs, Anselin & Varga, 2002). Nevertheless, there is a positive tendency observable in the region not only in the data with more patents being granted but also in practical developments. As recent studies show, technology laboratories are being established for holistic and affordable, local Precision Agriculture and Smart farm Managements solutions in the states on the Western Balkan (Taganakis et al., 2018). Nevertheless, the results of this study call for a strong and fast transition towards sustainability in knowledge, society and the economy in total – based on science-based research to harness the ongoing trends (Fagerberg, 2018). Well managed policies could alleviate the issues and help the countries to transform what is typically still one of the largest sectors by bound labour but kept in low productivity due to small, individualistically working family farms (Verhapi & Sabotic, 2015). This would not only help the single households out of unproductive subsistence agriculture but would also free up land for recreational and ecological purposes while generating income to strengthen the countries' economies. A stable market without too much price volatility is what productive agriculture mostly relies on to be profitable. This said, the same study to be run in five to ten years might deliver stronger results, in the relationship of Precision Agriculture Technology innovation on the economic productivity of a country.

7. References

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8. Appendix

8. Appendix

Appendix A: Overview of Theory Definitions

Productivity	Total Factor Productivity: Jorgenson & Griliches, 1967 "Measurement of total factor productivity is based on the economic theory of production. The rate of growth of total factor productivity is defined as the difference between the rate of growth of real product and the rate of growth of real factor input. The rates of growth of real product and real factor input are defined, in turn, as weighted averages of the rates of growth of individual products and factors" Agricultural Productivity: Capalbo & Antle, 2015 "A two-stage procedure. In the first stage a total or multifactor productivity index is computed [on farm level], usually for different regions and time periods. In the second stage, regression analysis is used to decompose this productivity measure by regressing it on research, extension schooling, and agricultural input variables" (Ch. 10)
Innovation	OECD/Eurostat, 2018: Oslo Manual p. 20: "An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)." Nordhaus, 1969: "Benefits of patents as a solution to the market failure associated with the inappropriability of knowledge against the welfare cost due to the restriction on the use of the knowledge generated, and this tradeoff is optimized by patent"

	<u>*OECD (2019) on patents*</u> “Patents are a key measure of innovation output [or input], as patent indicators reflect the inventive performance of countries, regions, technologies, firms, etc. They are also used to track the level of diffusion of knowledge across technology areas, countries, sectors, firms, etc., and the level of internationalisation of innovative activities. Patent indicators can serve to measure […] productivity […] of a specific technology/industry.”
Sustainability	<u>Brundtand Report, 1987 p.8:</u> sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs” considering “economics (“profit”), environment (“planet”), and well-being of humans (“people”). <u>Dietz & O’Neill, 2013:</u> “The ability of the economy to function within the capacity provided by the earth’s ecosystems”
Green (Eco) Innovation	<u>Rennings, 2000</u> “Eco-innovations are all measures of relevant actors (firms, politicians, unions, associations, churches, private households) which: develop new ideas, behavior, products and processes, apply or introduce them and which contribute to a reduction of environmenta burdens or to ecologically specified sustainability targets. Their nature can be technological, organizational, social or institutional.” <u>Kemp & Pearson, 2008:</u> “Eco-innovation is the production, application or exploitation of a good, service, production process, organizational structure, or management or business method that is novel to the firm or user and which results, throughout its life cycle, in a reduction of environmental risk, pollution and the negative impacts of resource use (including energy use) compared to relevant alternatives”. <u>Horbach, Rammer & Rennings, 2012</u> *“*product, process, marketing, and organizational innovations leading to a noticeable reduction in environmental burdens”

Sustainable Entrepreneurship	Cohen & Winn, 2007: “Sustainable Entrepreneurship is the examination of how opportunities to bring into existence future goods and services are discovered, created, and exploited, by whom and with what economic, psychological, social and environmental consequences” Dean and McMullen, 2007 Sustainable Entrepreneurship is the process of discovering, evaluating, and exploiting economic opportunities that are present in market failures which detract from sustainability, including those that are environmentally relevant”
Sustainable Agriculture Technology	Barnes 2002: “Technology that yields “productivity growth which carries no negative external effect”
Precision Agriculture	Van Evert et al., 2017: “Precision Agriculture (PA) – classified as recording, reacting or guidance technique - is the scientific domain that deals with management of spatial and temporal variability to improve economic returns and reduce environmental impact. For farmers, PA is expected to lead to an increase in profitability; for society, PA is expected to lead to increased sustainability” Balafoutis et al., 2017: “Precision agriculture practices using high-tech equipment has the ability to reduce agricultural inputs by site-specific applications, as it better target inputs to spatial and temporal needs of the fields, which can result in lower greenhouse gas emissions. Kempenaar et al., 2017 “Precision agriculture is doing the right thing, in the right place, at the right time, in the right way based on observing, measuring and responding to inter- and intra-field variability in crops”

	Digital Agriculture as a more modern subtopic by van Es & Woodard, 2017: "deployment of computational and information technologies in farming, which will play a key role in achieving innovation goals such as desired outcomes of digital agriculture being more productive, profitable, and sustainable systems."

Appendix B: Setting the Scene for striving productivity: Diffusion and Structural Change in a suitable policy framework

The seemingly stringent relationship between innovation and output variation is in fact a small thread within a large field of interwoven strings of changes in allocation of resources or technological change and a variation of output. This thesis will try to show the first one to outline this connection in the agricultural context was Solow (1957). In his seminal paper, he proved on an aggregate level that technological change would explain variations in output, in addition to invested capital (Solow, 1957). The course of this chapter will show that innovation is exactly such a technological change. This section now shows metaphorically which neighbouring strings in this net could have an influence on productivity in agriculture but that will be not analysed in detail within this study. The growth process of an industry within the economy defined by Paul Romer (1990) in his endogenous growth theory, is consisting of increased outputs arising from a combination of an efficiently organised labour force and – more importantly – technological change. This endogenous model of growth explains structural change due to the spread of technology, because the returns on investments partly flow into public funds that can then foster development on institutional level. Productivity growth, hence, is a result of endogenous innovation decisions; strongly influenced by cross country determinants. Over the past quarter century connectivity has increased to levels thought to be impossible and internet that is available at all times nearly everywhere is also very favourable to innovation and diffusion. This more egalitarian ability to access infrastructure has expanded the world's technological frontiers to regions that were unable to catch up before (Keller, 2004). But not only infrastructure has enabled technological change at a high pace. Jaffe, Newell and Stavins, (2005) argue that technological change is mainly influenced by intrinsic motivation and guided according to the evolutionary theory of path dependent idea development. The market failure, which has a certain corrective momentum during in the state of technological change towards environmentally adequate technologies expresses itself in a double externality problem. On the one hand, there are the positive externalities of knowledge spillovers and diffusion mostly in early stages of innovation and then there are the negative externalities caused by unfavourable network effects in the diffusion phase of innovation. In addition to a freely expanding technological change, innovativeness needs to be supported from a regulatory side to be able to flourish with an impact on productivity (Rennings, 2000). Policy, therefore, needs to find the right mix and should use interventions as an incentive for innovation. Therewith, regulators can have a real impact on transforming the role of policy form being a harming substitute to uncontrolled development to a fruitful compliment of the same. Innovation policy has the ambition to increase the overall innovative performance of an economy (Lundvall & Borrás. 2005) without unbalancing the fragile equilibrium of supply and demand especially crucial in the primary sector when capping prices on either the top or the bottom as the extreme example of the so called "butter mountains" of the late 1970s show (EC, 2015).

Appendix C: Description of sourcing, transforming and merging and the decision process & Tabled overview about all variable descriptives

Appendix C.1: Detailed Description of Data Sourcing Processes

The data was obtained from different sources that had to be transferred to excel, cleaned, rebranded, reshaped and finally merged to build a dataset suitable for an in-depth analysis of the agricultural sector in Eastern Europe. Conventional Agricultural Indicators are from the *FAOstat*[1] database. This contains the *Net* (and *Gross*) *Production Index per capita,* the *AG Net* (and *Gross*) *Production Value,* the *Land used for Agri* in general and *Land used for Crops* in particular and the amounts of *Nitrogen Fertiliser* applied on the fields. Indicators related to sustainability, conventional innovation, green innovation, R&D expenditures, ecology in agriculture and some demographics are from the *OECDstat*[2]. This includes variables such as the *Agri Energy Consumption*, *CO_2 emission per capita, Production CO2 emission per capita,* patent data such as *Total US-Granted Patents, Agri US-Granted Patents, PSF-Agri Patents (US-Granted)* for special agricultural technology related inventions, the data on environmentally related invention such as *Environmental Patents* or *Green Patents per capita.* The last group of patents from the *OECD* was the demographics like *Population, Population Density* or the *real GDP per capita*. For more demographic data and primary sector combined value added for Agriculture, Fishery and Forestry, the *World Bank*[3] statistics with indicators such as the *Agri Empl. Ratio* or the *Primary per Worker Value Added* are integrated.

[1] http://www.fao.org/faostat/en/#home
[2] https://stats.oecd.org/Index.aspx?DataSetCode=GREEN_GROWTH#
[3] https://data-worldbank-org.eur.idm.oclc.org/

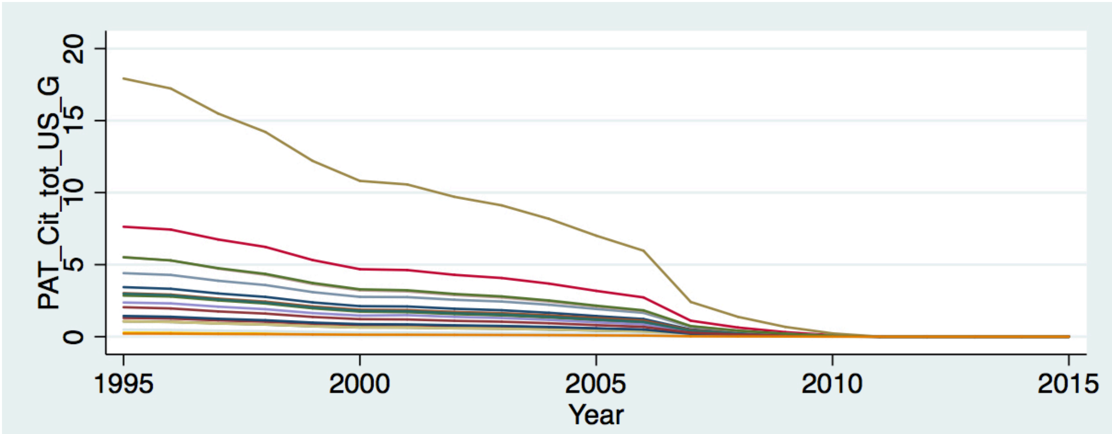
Obtaining patent data was itself more complex and different sources were checked before using *OECDstat* for patents and the *National Bureau of Economic Research* (NBER)[4] for patent citation data. The *OECD* collects patent data from the three major offices for intellectual property of their members and other countries by an own specific algorithm for sorting and displaying (further explained in Appendix D), namely the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO) and the Japanese Patent Office (JPO). Of course, this leaves out the Chinese and the South Korean, but given the area of investigation this will not bias the analysis. The patent office chosen to analyse the innovation patterns by patent statistic in a region without any major office (Eastern Europe) is the one from the United States. The USPTO shows a ratio of circa 50 per cent non-US residents in the database, which helps the present study to have enough data on the region of interest being the country of resident of the applicant. Additionally, it is the largest database on technological innovation with a constantly and strongly increasing number of filings and 256 IPC classes covered. Additionally, does no firm wanting to become a global player in its business ignore the American market and hence files a patent also there. The European Office in comparison, which might be the first intuitive choice due to geographical proximity, is significantly smaller in the amount of information offered is nearly nonexistent. Although the countries of residents show a great diversity, its technological diversity lacks behind the other databases (Kim & Lee, 2015). Innovations in the agricultural sector can be assumed to be done by companies as assignees at least, because the products are capital intensive and the market does not provide the structures for individual lone wolf breakthroughs; hence the individual inventor is not relevant here leading to selection patents only by applicant. The OECD Database additionally offers the possibility to do the patent count at the date of grant. In classic patent literature the first filing date called priority date is taken and then lagged, but the date of grant appears to be more accurate due to two reasons. It firstly considers only patents really granted and hence very likely to turn into commercialised innovations and secondly it already includes the needed lagging. The reference date in the OECD database is 2013, but the data form the OECD is complete up until 2015 only for the USPTO data; providing another reason to work with this patent offices' entries.

The process for the also important patent citation count worked differently as they were sourced from NBER. Although the *NBER* is a widely recognized and renowned provider of patent data, it was difficult to integrate. The main publicly available dataset only covers US-granted patent citations until 2006, which makes it reliable until 2001. This was then extended by another not publicly available dataset from the same source and provided by Associate Professor A.S. Bhaskarabhatla of ESE Rotterdam. It covers citations until 2013, with reliable numbers until 2010. This together is then reliable citation data until 2010.

[4] https://www-nber-org.eur.idm.oclc.org/patents/

Nevertheless, the missing two years were assumed to have received zero citation to make it a complete variable. Figure AC1 shows the development per million residents. The main reason, why the citations are not chosen as the regressor in the principal model against the literature (e.g. Hall, Jaffe & Trajtenberg, 2005) is the inaccurate numbers for the last quarter of years and its lower level of detail in narrowing it down according to the hypotheses. The NBER data unlike the OECD one does not distinguish the country of residence for the applicant, only for the inventor. So, it cannot be divided by region as needed and will, therefore, only work as a robustness check for the regressions.

Figure AC1: Course of Total Patent Citations (US-Granted) from 1995-2015 in all 19 countries



For both databases, the patents on Precision Agriculture had to be filtered out from the total. The best way to do so is to use the three-digit code of the International Patent Classification (IPC)[5] by the World Intellectual Property Organisation (WIPO). Because there is not one category exactly named Precision Agriculture Technology, the field was approached in two steps. First, the whole area of *A01 - Agriculture; Forestry; Animal husbandry; Hunting; Trapping; Fishing* is analysed for *Agricultural Technology* without specific focus on sustainability or the ecology as such. Afterwards, in a narrower sense, the subcategory *A01C – Planting, Sowing, Fertilising* fits best to the theoretical definitions of Precision Agriculture Technology (see Appendix A) and the available control variables.

[5] World Intellectual Property Organization. (2019). International Patent Classification. Retrieved May 30, 2019, from https://www.wipo.int/classifications/ipc/ipcpub/?notion=scheme&version=20190101&symbol=none&menulang=en&lang=en&viewmode=f&fipcpc=no&showdeleted=yes&indexes=no&headings=yes¬es=yes&direction=o2n&initial=A&cwid=none&tree=no&searchmode=smart

Unfortunately, the values are rather low for applicants being residents in Eastern Europe. This categorisation also has its drawbacks exemplified by the use case patent of YARA (e.g. US6444975B1), which is clearly a Precision Agriculture Technology for fertilising by theoretical definition. Still, it is filed in categories also outside A01C – namely H01J. For younger patents since 2006, the patent offices are more aligned on also classifying them more according to the field of usage for the patents (Haščič & Migotto, 2015). For the older ones it is out of scope of this thesis to cover this widespread classification according to underlying physical technology. Naturally, in patents the region of application does not have to be the same with the country of residence of its inventor as technology works borderless and diffusion is especially fast (Keller, 2004) For the present study, this translation however would have been out of scope. This is why it was decided to assume that patents by regional technology companies are more likely to be applied in the specific country and might therefore have the highest impact on the productivity there.

The following paragraph will explain the steps to bring together all the different data into one dataset for the analysis after the theoretical choice is explained above. First, the Comma Separated value text files from the statistical pages had to be transferred to Excel. Before being able to use the datasets in *STATA*, they needed to be aligned in Excel, meaning that a coherent variable language had to be established. To reach that, I created a year variable, a three-letter country abbreviation (e.g. ALB for Albania etc.) and a unique country- year variable like *ALB1995* for Albania in the first year of observation. Thirdly, after having the unique ID variable in place, the data was reshaped in *STATA* to a wide format and exported again for second round cleaning with all the variables easily comparable n the same format to spot missing observations or issues with decimals. In order to come over some data misses, I helped myself with certain tricks: Most prominently was that Montenegro often showed missing values from 1995 to 2005 due to the fact that is was one country back then with Serbia after Yugoslavia was resolved. In the cases that there was not an explicit *Serbia & Montenegro* country available at the source I assumed the Serbia data contain the values for Montenegro intrinsically. In both cases I took a ratio from bot country's first year in separation – namely 2006 – and applied this to the missing years to find out the split between Montenegro and Serbia. This method was applied in the variables of the *GPI/NPI* group, *Nitrogen Fertiliser*, *Land used for Agri, Production CO2 emission per capita, Value Added Ratio* and *the Agri Energy Consumption.* In the variable *CO_2 emission per capita*, both Serbia and Montenegro values were missing. To cover that, the five-year average growth from 2006 on was reverted to the previous years for estimation. Additionally, all values for 2015 I estimated by extrapolating the 2013 to 2014 annual growth. Also with a five years average reverted growth rate were the 1995-2005 values for Serbia and Montenegro in the *Population* variable estimated. In the OECD Patent and Environment Patent Datasets the Country *Former Republic of Yugoslavia* is taken as proxy for Albania, Serbia and Montenegro with the same values and then also calculated by the ratio as before. Finally, the clean and complete datasets were merged to establish one final dataset with 399 lines of observations and over 130,000 data points already being in the needed panel data long format.

Lastly before being able to start the analysis, the variables had to be grouped according to the theoretical framework and fitting to answer the main research question. According to the theory segmentation used in the *Theoretical Framework (Chapter 2)*, the most important category and hence first group to mention is productivity. It contains output related agricultural indicators that will be used to define a term of productivity per worker in the agricultural sector. Syverson (2011) argues that production output would be the best measure for productivity. In the manufacturing companies that Syverson observed this was difficult due to multifactor inputs. In agriculture, however, it is more achievable because inputs are comparable and not costly for all crops but the processes of controlling and supervising the growing make the output differ. The second important group is the innovation section. The literature is split up in two streams when analysing it on country level. One is looking on the innovative input such as Research and Development investments (Jaffe, 1986; Hall, Mairesse & Mohnen, 2010). It is a commonly used measure and get easily be linked to policies; in the case of this thesis to the EU three per cent of GDP invested per annum bottom line by 2020 for example (Janger et al., 2017). The other stream is patents. They are considered as being very objectively measurable innovation output determinants of things already implemented and executed (e.g. Griliches, 1990). The Oslo Manual, which explains how to interpret innovation data, points out that patents should be used as efficient measures for the forthcomings of innovation not only in conventional terms but especially for ecological purposes (OECD & EUROSTAT, 2015). The data in this study is sourced from the OECD. The institution uses its own algorithm to collect patents according to the International Patent Classification[6] rules (WIPO, 2019) from the main offices around the globe. The exact mechanism is explained in the Appendix E.1. The third group that needs to be mentioned quickly are the demographics giving information about the population density and the development status and income structure. Additionally, there are two binary variables controlling for the institutional membership in the EU and OECD: This said, the attention in the data will now be directed towards the agricultural determinants that are again split into three groups. The first specification and forth overall theoretical group is the social component of agricultural productivity. The main measure here is the labour force involved because this indicated how much of the workforce is bound to often subsistence agriculture that is very low in productive output and blocks the way toe wage earning professions for family members (Gollin & Rogerson, 2014). The second big group of

[6]https://www.wipo.int/classifications/ipc/ipcpub/?notion=scheme&version=20190101&symbol=none&menulang=en&lang=en&viewmode=f&fipcpc=no&showdeleted=yes&indexes=no&headings=yes&notes=yes&direction=o2n&initial=A&cwid=none&tree=no&searchmode=smart

indicators in this theoretical field is the land use for agriculture. How much of the surface of a country is consumed by the agricultural activities or more precisely the crops grown on it. The conversion rate also gives revealing information of whether the sector is still growing a lot in size of arable land or not. In the countries under scrutiny here, the value from 1992 to 2015 has been below three per cent conversion from natural land to cropland. This proves the fact that also already in Eastern Europe now the time has begun to use this area as efficiently as possible to even be able to reduce the area in the future. As fifth block, there are measurements for agricultural output in its conventional economic terms. This means it covers value and weight measured output determinants and value-based efficiency as it is used by Pardey, Alston & Ruttan (2010). The sixth and last group embodies the ecological harm and sustainability determinants of agriculture represented by resources needed as inputs in the crop growing process. These comprise water for irrigation, different types of fertilisers and pesticides ensuring crop health as well as the energy consumption both electric and fuel for the heavy machinery (Eberhardt & Vollrath, 2018). The section moreover includes air pollution, soil depletion and area sealing by construction work.

Appendix C.2: Descriptive Statistics, Sources and Definitions of Variables

Variable Name & Description	Variable Definition	Source	Theory Group	Type / Scale	Obs	Mean	Std.Dev.	Min	Max
DEPENDENT *(y)* - Productivity									
Gross Agri Production Index per capita *(GPI_Ag_pc)*	Gross Production Index (Number) for agricultural sector per capita	FAOstat	Productivity	Index number, per capita	399	101.37	43.6	59.24	907.2
Net Agri Production Index per capita *(NPI_Ag_pc)*	Net Production Index (Number) for agricultural sector per capita	FAOstat	Productivity	Index number, per capita	399	100	18.58	59.53	190.53
Labour Productivity[7]	Value Added in Agriculture per worker employed in the sector calculated	interact	Productivity	Percentage	399	.63	.34	.16	2.15
MAIN INDEPENDENT *(x)* - Innovation									
Total US-Granted Patents *(PAT_TOTAL_GR_A_US)*	Patents granted at USPTO by Applicant(s)'s country(ies) of residence per mn residents	OECD[8]	Innovation	Count, Per million	399	1.86	3.52	0	23.31
Agri Patents (US-granted) *(PAT_A01tot_GR_A_US)*	Agricultural patents (A01B-P) granted at USPTO by Applicant(s)'s country(ies) of residence per mn residents	OECD	Innovation *(Ag Tech)*	Count, Per million	399	.02	.06	0	.52
PSF-Agri Patents (US-Granted) *(PAT_A01C_GR_A_US)*	Planting, Sowing & Fertilising Patent Granted by USPTO & sorted by Applicant(s)'s country(ies) of residence per mn residents	OECD	Innovation *(Sustaibale Ag-Tech)*	Count, Per million	399	0	.01	0	.19
Total Patent Citations (US-Ganted) *(PAT_Cit_tot_US_G)*	Citations per patent filed at USPTO in respective year from worldwide applicants ALL industries	NBER	Innovation *(Robustness)*	Count, Per million	399	1.31	2.34	0	17.92
Agri Patent Citations (US-Ganted) *(PAT_Cit_A01_US_G)*	Citations per patent filed at USPTO in respective year from worldwide applicants in “agriculture; forestry; animal husbandry; hunting; trapping; fishing”	NBER	Innovation *(Robustness)*	Count, Per million	399	.51	1.19	0	9.84
CCM-Tech Patents (US-Granted) *(ENV_PAT_GOODS)*	Patents granted for Climate change mitigation technologies in the production or processing of goods at USPTO by Applicant(s)'s country(ies) of residence per mn residents	OECD	Innovation *(Green)*	Count, Per million	399	.03	.1	0	.81
Environmental Patents US-granted	All enviromentally related Patents granted at USPTO by Applicant(s)'s country(ies) of residence per mn residents	OECD	Innovation *(Green)*	Count, Per million	399	.28	.77	0	9.1

[7] Based on Gilli, Mancinelli & Mazzanti (2014) as it is able to capture sector heterogeneity well and suits the Triple Bottom Line framework

[8] OECD has own Algorithm to compile the patent data (Haščič & Migotto, 2015) and see details in below description

(ENV_PAT_tot)									
Green Patents per capita *(GPAT_pc)*	Development of environment-related technologies, inventions per capita	OECD	Innovation *(Green)*	Count, Per capita	399	1.19	1.67	0	12.1
Green Patents per million inh. *(GPAT_pmn)*	Development of environment-related technologies, inventions per million residents	OECD	Innovation *(Green)*	Count, Per million	399	9.48	15.06	0	116.09
Green Patent Ratio *(GPAT_at)*	Development of environment-related technologies, % all technologies	OECD	Innovation	percentage	399	9.87	9.98	0	100
CONTROLS I - Demographics									
Member of the OECD *(OECDMember)*	country is a member of the Organisation of Economic Cooperation and Development (1=yes)	OECD	Demographic	Binary	399	.22	.42	0	1
Member of the EU *(EUMember)*	Country is a member of the European Union (1=yes)		Demographic	Binary	399	.29	.46	0	1
Population Density *(POP_den)*	Inhabitants per square kilometre	OECD	Demographic	Continuous	399	83.15	30.46	29.01	134.45
real GDP per capita *(GDPreal_pc)*	Inflation Adjusted per capita measure of the Gross Domestic product of the value of all produced goods and services per year on constant 2010 US Dollar values	OECD	Demographic	Continuous, 2010 dollar Per capita	399	14101.7 6	6972.87	1748.18	30070.29
lnGDP_pc	Natural logarithm of above values	OECD	Demographic	Natural logarithm	399	9.4	.6	7.47	10.31
CONTROLS II – Social									
Agri Empl. Ratio *(Empl_Ag)*	Employment in agriculture (% of total employment) (modeled ILO estimate)	World Bank	Structural Change	Percentage	399	16.81	11.79	2.75	51.03
Agricultural Land *(Ag_Land)*	Agricultural Land in total land area	FAOstat	Structural Change	Percentage	399	47.12	15.2	16.47	77.72
Land used for Crops *(Cropland_Land_area)*	Cropland share in total land area	FAOstat	Structural Change	percentage	399	32.03	15.27	.93	66.4
CONTROLS III - Economic									
Crop Output in Area (pc) *(CROP_out / CROP_pc)*	Total Crop Output by crop in tonnes (per capita)	OECD	Productivity	Continuous, Total tonnes	399	875017	1400000	278	7050000
lnCROP_pc	Natural Logarithm of above variable per capita	OECD	Productivity	Natural logarithm	399	-2.96	1.36	-8.92	-1.25
Wheat Production (pc)*(PROD_wheat/pc)*	Production per crop and per hectare (wheat most complete) (per capita)	OECD	Productivity	Continuous, Total tonnes	399	2950000	4430000	752	2.65e+07
Value Added Ratio Agri	Value added in agriculture, % of total value added per	OECD	Productivity	Percentage	399	9.35	7.06	1.68	55.81

(AG_VA)	capita								
CONTROLS IV - Environmental									
RTA in Green Tech *(GPAT_RTA)*	Revealed (relative) technology advantage (RTA) in environment-related patents ("specialisation index")	OECD	Innovation	Continuous, Index	399	1.27	1.42	0	15.24
CO2 Emissions per capita *(CO2_em_pc)*	CO2 emissions (metric tons per capita)	OECD	Sustainability *(Air Pollution*	Continuous, tonnes per capita	399	5.68	2.88	.49	
Production-based CO2 emission per capita *(CO2_PBEMCAP)*	Production-based CO2 intensity, energy-related CO2 per capita	OECD	Sustainability *(Air Pollution)*	Continuous, tonnes per capita	399	5.43	2.76	.45	14.28
Agri Energy Consumption *(ENERGY_cons_ag)*	Energy consumption in agriculture, % total energy consumption	OECD	Sustainability *(Pollution)*	Percentage	399	2.83	2.06	0	11.28
Nitrogen Fertiliser *(FERT_Nitrogen)*	Nitrogenous Nutrient Fertilizers (N total) in Agricultural Use	FAOstat	Sustainability *(Soil Pollution)*	Continuous, Total tonnes	399	196398.8	254571.9	948.42	1180000
FERT_pc	Above variable per capita in tonnes per country	FAOstat	Sustainability	Continuous,	399	0.02	0.01	0	0.06
lnFERT_pc	Natural logarithm of Nitrogen Fertiliser amounts per country in tonnes per capita	FAOstat	Sustainability	Natural logarithm	399	-4.28	1.08	-7.65	-2.76

* Those variables mainly used in the models are put in bold

Appendix D: The development towards smart decision making in Precision Agriculture Technology – Trends in Data Usage and **t**he Case of YARA as an example for patenting

The status quo in development and the future path of on-field technology is influenced by data collection, storage and usage. In agriculture however it has remained rather out of the public debate for a long time, although the technology is in place for quite some time now. The next section will discuss the current state of the literature assessing risk and possibilities arising from the technology related to sectoral profitability and present a patent and technology case of fertiliser producer YARA. Data ownership is of high importance for the food sovereignty of a country. There is no control over field data if few large corporations hold all rights on data from sensors on the fields (Fraser, 2018). Over 40 zettabytes of data will be collected by agricultural technology providers in the coming years (Van Es & Woodard, 2017). Poppe, Wolfert, Verdouw and Renwick (2015) see huge consolidation movements ahead. The localisation of sustainable farming with direct a link to the customer through technology development will arrive as ICT implementation and Big Data usage in Agri-Business advance and collaboration and data exchange facilities become more prevalent. The aspect of local supply chains is especially important for developing markets. This claim is supported by Gollin and Rogerson (2012) in their arguments that higher transportation costs keep people from moving into other jobs, because they need to keep up their own supply with subsistence farming activities. In a previous work, Gollin (2010) argues that only when productivity is strengthened, the population working in small scale subsistence agriculture can become active in value adding processes of other industries. However, the ongoing expansion of Precision Agriculture bears chances as well as risks. The agricultural sector could become more of a provider of data use cases for technology companies and storages and the control over this information will be an issue (Fraser, 2018).

Theoretic cases outlined by Janssen et al. 2017 generally call for more elaborate modelling in the code of the present technology. With the help of use cases the group of previously named authors pictures the next generation of connected and sustainable farming harnessing data optimally. Three of them can give an outlook on the relevance for the econometric study of this thesis. The reader needs to picture the following scenarios of possible users of modelling for research on Precision Agriculture Technology. The first is "*A researcher at an international agricultural research station, who tries to develop new technologies for sustainable intensification and wants to assess different technology options.*". This person seeks a complexity reduction in the field of technology usability – at best with open data systems and interconnectedness – for a more flexible workflow. The second case is *"An investment manager at a donor organization who seeks to evaluate different project proposals to identify the projects most likely to be effective."*. This person also seeks a complexity reduction in the field of technology usability. In terms of data the person aims for more use and implementation of open data and interconnectedness, usage of new sources. It should be accessible rather through an app than desktop based. The last case is "*a farm advisor in precision agriculture who assists farmers in using high tech data streams through farm management software."*. Usability wise, this use case seeks for better adoption to user requirements. The person has high prefernces regarding data privacy, security, sovereignty and the usage of new sources; at best displayed in an application. It becomes apparent that the difficulty of this technology in the future will be to align it on the different requirements of user groups together with concerns on data security and national sovereignty (Janssen et al., 2017, 202-204).

Inspired by the research of Zvi Griliches on the hybrid corn (Griliches, 1960) and Petra Moser and her colleagues on the effect of patents and their citations to show single invention spread and importance (Moser, Ohmstedt & Rhode, 2017) the effects of innovation are visible also in an even more narrow field. *Yara*[9] is the leading global provider of fertilizers (mainly nitrogen based) and has dedicated itself to combat agricultural pollution. This said, they started developing Precision Agriculture technology already in the 1990s and applied for their first patent on a tractor-mounted on-the-go nitrogen sensor for fertiliser control in 1999 (US 6444975 B1), which got filed in 2002. Until 2006, three more on improved techniques followed. Combining this with the standard market introduction patterns from innovation theory (REF) the current state of the N-sensors in Eastern Europe can be described as being in the product life cycle status of … (answer depending on market intel form YARA). Their N-Sensor tool is widely accepted and used in practice. This third Hypothesis does not only conclude the results from the first two hypotheses in a concrete example, but it also brings this thesis to a level of applied research needed for a broad understanding, further research and policy implications

In comparison, the local Eastern European research company *BioSense*[10] supported by the Wageningen University and Research aims to implement a holistic portfolio of remote sensing and site-specific technology into an emerging market into a prosperous region with great future potential.

The case of Yara has shown the impact of data usage by companies. The field was completely unregimented and free in the past. But as scholars already point out this will change in the future for the sake of protecting the farmers privacy and a country's sovereignty over the sensitive mass of data concerning the alimentation of its citizens.

[9] https://www.yara.com

[10] https://biosense.rs/?page_id=6597&lang=en

Appendix E: This section lays out the systematics and arguments behind using patents as an indicator for innovation, why the USPTO patents by date of grant where chosen, and how the group of Environmental Patents is constituted

Appendix E.1: Patent Data Sourcing, Definitions and Categorisation

To measure innovation, there are two commonly used ways indicated in the literature of aggregated country-level analyses. One is government expenditure on R&D (Jaffe, 1986; Hall, Mairesse & Mohnen, 2010), which is not suitable here as the intention of the study is evaluate the innovativeness of a country according to executable and innovation ready to implement. The latter is reflected well in patent count data (Kleinknecht, van Montfort & Brower, 2002). In the OECD database used to source the patents[11] the advantages and disadvantages of patents are also clearly listed. The main point in favour is that they do not also capture the direct innovative output of a region, industry or technology type, but also allow keeping track of technology diffusion as an indicator for structural change and most importantly indicate the effectiveness of R&D inputs brought forward into a tangible invention. Patents show both input and output measure qualifications (OECD, 2009). Additionally, they are a broad and extensive source of rather objective information about all types of technologies, claims and follow up inventions that used the primary to invent upon (Moser, Ohmstedt & Rhode, 2017, OECD, 2019,a). The exact, concluding definition of the same source is as follows:

"Patents are a key measure of innovation output [or input], as patent indicators reflect the inventive performance of countries, regions, technologies, firms, etc. They are also used to track the level of diffusion of knowledge across technology areas, countries, sectors, firms, etc., and the level of internationalisation of innovative activities. Patent indicators can serve to measure […] productivity […] of a specific technology/industry." (OECD; 2019a)

Notwithstanding, there are also drawbacks and downsides to this measure. The most prevalent is the skewedness of the information caused by to opposite reasons. On the one hand side, filed and even granted patents may not reach the realisation stage and hence do not unfold their full potential of societal benefit. On the other hand, there is lack of patents being filed in many cases due to a lack of appropriability of the financial and organisational efforts or more efficient mechanisms such as secrecy, lead time or trademarks (Wright, 1983, Cohen, Nelson & Walsh, 2000).

[11] See extensive description in Appendix C.1

To finish the general patent descriptions a few arguments on why the OECDstat database and on the detailed selection will be outlaid. As mentioned in the main body and Appendix C.1 already, the patents were not collected from the single patent offices but rather from the statistical site of the OECD that collects and displays them very comprehensively by office and filing date (OECD, 2019a). It collects mainly data form the EPO, the USPTO, the JPO and for specialities such as patents filed below the Patent Cooperation Treaty or patents belonging to Triadic Patent Families representing subsets that are filed under all three offices for the same invention. In patent filing there are different important distinctions to make on the steps in the process. The first step is the filing of the application in her country of residence also called the Priority Date and being the closest to the real invention date. This date is often used to measure inventive activity. The second step is the twelve months' time range, in which the inventor can decide whether to apply for protection also in other countries. The day this is done is called the Application Date of a patent and is seldomly used for analysis as there is a bias between residents and foreigners. After 18 months, a patent gets published. The third and last step is the moment the filing is finally granted by the respective office once it confirms all necessary criteria are fulfilled (Block, Fisch, Hahn & Sandner, 2015). The Date of Grant best reflects the administrative delay of up to ten years from priority date. It becomes apparent that the USPTO is the most complete ranging from 1976 for filings and grants up to 2014 for priority date filings, 2015 for the application date and 2017 for granted patents. The decision for this study was on the date of grant due to two reasons. First to count only patents that have the most chances to be commercialised and offset one of the limitations described before and secondly, to already include the three to five years lag from first filing to final grant without the need to apply a standardised "one year fits them all approach" on priority date data afterwards.

Appendix E.2: Environmental Patents

Now, the establishment of the specific group of *Environmental Patents* is going to be explained based on the information provided by the OECD (2009, 2019a). I do this in such detail because this kind of grouping would also be advantageous in the agricultural sector for future research, as it grasps the diversity and complexity of the patent filing processes and classifications holistically; an effort out of scope for a single researcher in limited time. For the classification the OECD uses the worldwide PATSTAT search engine of the EPO. To be able to collect the patent information below the Green Patent and Environmental Patent label, the institution developed a unique algorithm to go through more than 200,000 identifiers and keywords for environmental importance. Additionally, manual search is applied for a final, sophisticated elaboration (Haščič & Migotto, 2015). The fields of technology covered by the search are only patents of invention regarding environmental management, water-related adaptation and climate change mitigation (OECD, 2019a).

Appendix F: Industry Independent Comparative Patent Statistics from the World Intellectual Property Organisation and OECD gives an Overview about patenting developments around the globe and in the region of analysis

Appendix F.1: Utility model applications and grants by office and origin, 2016

Source: WIPO Statistics Database, September 2017.

	Applications by office			Grants by office		
Name	Total	Resident	Non-resident	Total	**Resident**	Non-resident
Albania	4	3	1	1	**0**	1
Belarus	416	353	63	328	**265**	63
Bosnia and Herzegovina				No Data		
Bulgaria	462	450	12	217	**208**	9
Croatia	83	77	6	70	**68**	2
Czech Republic	1,264	1,199	65	1,187	**1,124**	63
Estonia	61	55	6	52	**38**	14
Greece	23	20	3	19	**17**	2
Hungary	304	282	22	108	**98**	10
Latvia				No Data		
Montenegro				No Data		
Poland	1,151	1,084	67	674	**638**	36
Republic of Moldova	156	154	2	122	**121**	1
Serbia	61	54	7	40	**36**	4
Slovakia	359	300	59	363	**322**	41
Slovenia				No Data		
Ukraine	9,584	9,470	114	9,044	**8,931**	113

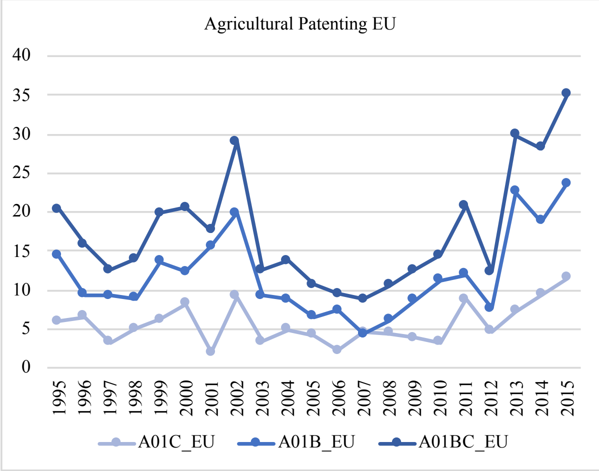
Appendix F.2: Trend in patent applications for the USPTO

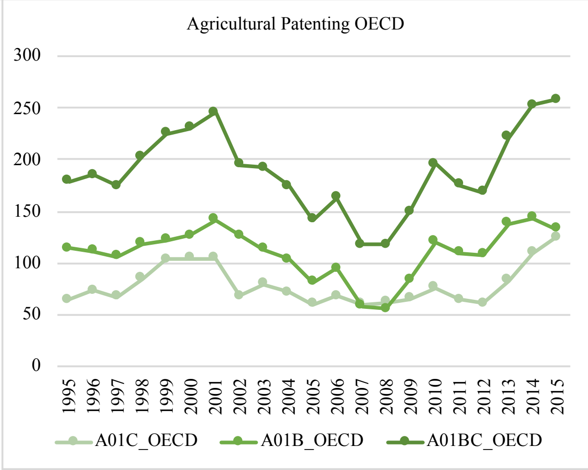
Note: The office was selected based on their 2016 totals.

Source: WIPO Statistics Database, September 2017.

Year	U.S.	Growth rate (%)
1995	228,142	2%*
1996	211,946	-7%
1997	220,496	4%
1998	236,979	7%
1999	265,763	12%
2000	295,895	11%
2001	326,471	10%
2002	334,445	2%
2003	342,441	2%
2004	356,943	4%
2005	390,733	9%
2006	425,966	9%
2007	456,154	7%
2008	456,321	0%
2009	456,106	0%
2010	490,226	7%
2011	503,582	3%
2012	542,815	8%
2013	571,612	5%
2014	578,802	1%
2015	589,410	2%

Appendix F.3: Development of Patents Granted per year in the Agricultural Sector in the OECD and EU from 1995-2015 in all 19 countries of the sample





Appendix G: Matrix of correlations of all variables in not yet model-adapted (raw) scaling

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1) GPI_Ag_pc	1.0																										
(2) NPI_Ag_pc	.34	1.0																									
(3) PAT_TOT*	.03	.14	1.0																								
(4) PAT_A01tot*	.07	-.0	.35	1.0																							
(5) PAT_A01C*	-.0	.01	.01	.18	1.0																						
(6) PAT_Cit_tot*	-.09	-.24	-.15	-.10	-.04	1.0																					
(7) PAT_Cit_A01*	-.08	-.21	-.13	-.08	-.03	.93	1.0																				
(8) ENV_PAT_GOODS	.02	.1	.37	.23	.06	-.04	-.06	1.0																			
(9) ENV_PAT_tot	.08	.2	.70	.19	.05	-.12	-.11	.42	1.0																		
(10) GPAT_pc	.01	.14	.80	.30	.02	-.21	-.19	.31	.45	1.0																	
(11) GPAT_pmn	-.0	.09	.26	.15	.01	-.28	-.23	.10	.18	0.41	1.0																
(12) GPAT_at	-.02	.05	.03	-.02	-.00	-.08	-.09	-.00	.05	0.21	0.16	1.0															
(13) GPAT_envtech	-.04	-.04	-.03	-.04	-.01	.02	-.01	-.01	.00	0.13	0.09	0.97	1.00														
(14) OECDMember	-.03	-.04	**.46**	.27	.13	-.23	-.19	.17	.34	**.53**	**.57**	.05	.02	1.0													
(15) EUMember	.04	.26	**.49**	.26	.11	-.27	-.27	.17	.33	**.60**	**.44**	.10	-.01	.45	1.0												
(16) POP_den	-.05	-.12	.05	.09	.06	-.17	-.13	.04	-.04	.07	.37	-.01	-.00	.50	0.01	1.0											
(17) GDPreal_pc	.05	.23	**.60**	.28	.11	-.23	-.24	.31	.38	**.70**	**.42**	.04	-.03	.59	0.74	0.04	1.0										
(18) Empl_Ag	-.03	-.05	-.37	-.21	-.08	.11	.11	-.20	-.26	**-.46**	-.26	-.05	-.01	**-.42**	**-.42**	.29	**-0.67**	1.0									
(19) CROP_out	.04	.12	-.12	-.05	-.02	-.25	-.19	-.07	-.07	-.09	**.46**	.08	.06	.07	-.03	.15	-.16	.10	1.0								
(20) PROD_wheat	.06	.19	-.08	-.02	-.01	-.28	-.21	-.05	-.04	-.04	**.56**	.08	.06	.17	.05	.21	-.06	.03	0.97	1.0							
(21) AG_VA	-.05	-.15	-.36	-.19	-.05	.16	.18	-.22	-.23	**-0.48**	-.36	-.11	-.05	**-.43**	**-.51**	.14	**-.77**	.77	-.01	-.08	1.0						
(22) CO2_em_pc	.07	.14	.34	.01	.02	-.11	-.09	.18	0.34	**0.45**	.34	.04	.03	.48	.28	-.00	**.55**	**-0.60**	.15	.20	**-0.57**	1.0					
(23) CO2_PBEMCAP	.06	.12	.35	.02	.02	-.04	-.04	.18	0.32	**0.46**	.35	.03	.02	**.50**	.29	.04	**.55**	**-0.59**	.14	.18	**-0.57**	0.98	1.0				
(24) ENERGY_cons_ag	.09	.15	-.07	-.00	-.05	.08	.11	-.03	0.01	-.10	.10	.02	.06	.12	-.06	.13	-.13	.26	.10	.13	.17	-.01	.01	1.0			
(25) FERT_Nitrogen	.09	.2	-.6	.00	-.03	-.32	-.25	-.02	-.02	-.01	**.66**	.06	.03	.38	.12	.29	.10	-.08	**.67**	**.75**	-.22	.29	.28	.36	1.0		
(26) Ag_Land	-.01	-.09	-.27	-.05	-.02	-.13	-.07	-.20	-.17	-.28	.22	.09	.11	.10	-.19	**.49**	-.43	.38	**.54**	**.52**	.36	-.22	-.21	.14	.34	1.0	
(27) Cropland_Land~a	.03	.02	-.20	.01	-.00	-.24	-.16	-.14	-.10	-.18	.32	.08	.08	.21	-.07	**.52**	-.29	.31	**.58**	**.58**	.22	-.07	-.06	.28	**.43**	.90	1.0

* _GR_A_US

Appendix H: Model Derivation along the Multi Linear Regression conditions ahead of Hypothesis Testing

Before it was possible to analyse the hypotheses, the choice of the best estimator had to be completed. This follows the very first steps explained in the methodology section 3.2. Now, as the set of variables is defined, and fixed effects is the model of choice from theory, its validity against other estimation methods was probed. In the dataset all variables are linear, and the possible dependent variables are neither categorical r binary nor count variables. Therefore, multilinear regression is a probable estimation method. Wooldridge (2015) defines six conditions that must hold for all models to be valid. Some of them can be confirmed directly from the data, whereas others need to be tested in the course of this section. The first condition is linear parameters being present, which is fulfilled with the dataset (see Appendix C for reference). The second is a random sampling method, which is also given by the broad global data collection by the different sources described in Appendix C. The third one is requesting no perfect collinearity of the variables. This is tested with a Wald test on the regressions and delivers the result of jointly significant and not collinear sets of variables for all four regressions. The fourth condition is one of the most important: The zero conditional mean assumption. It supposes that the error term in a regression has an expected value of zero regardless the value of the explanatory variables [$E(u|x) = 0$]. Additionally, it has three sub conditions that need to be tested. The right specification of the functional form between the explanatory and explained variables, bias through omitting important factors in the error term – influencing both the right-hand side and the left-hand side of the regression – and reverse causality when the depend variable also influences the independent ones. These conditions will be tested in detail later. The fifth condition is inference. Meaning that the variances of all explanatory variables should be evenly distributed and equal to the one of the error term [$Var(u|x_1, x_2, ...x_k) = \sigma^2$]. This assumed homoscedasticity is necessary for a model to be efficient. It will be tested as well later on. The last condition – also regarding inference – is Normality. It requires the error term to be independent from the explanatory variables and to be normally distributed [$u \sim Normal(0, \sigma^2)$]. Tested with Kernel Density there is no issue detectable[12].

The most common models in panel analysis are the Random Effects and Fixed Effects Models. The latter splits the unobserved error term in two: the time variant and invariant elements. Time invariant unobserved effects are allowed to be arbitrarily correlated with the explanatory variables in each time period. Additionally, the method drops all between variation for the coefficient estimation and hence avoids omitted variable bias form those time invariant factors. This would make

[12] The check for normality is necessary in this panel, because it is on the lower end of the scale where a normal distribution of β can be assumed. The kernel density compares the density of residuals with the normal distribution. In the data, no infringing deviations can be detected.

Fixed Effects the right model if omitted variables are expected, which one can never be totally excluded. The main criteria for Random Effects is the unobserved heterogeneity condition, defining that the serially correlated error term shows the share explained by the total variation [corr (v_{it}, v_{is}) = $\frac{\sigma 2\ (\alpha)}{\sigma 2\ (\alpha)+\sigma 2(\mu)}$] This and the strict Zero Conditional Mean assumption [cov (x_{cit}, α_i) = 0] make it more restrictive than Fixed Effects. Random effects include both time variant and time invariant factors into the model; exploits both within and between variation accordingly (Wooldridge, 2015).

To decide between the two estimation types, the Hausman test was run (Stock & Watson, 2003). In the book, the primary task of the Hausmann test is described to detect endogeneity within the regressors. This would mean that the independent variables are influences by the error term. If this would prove right, an instrumental variable regression would be the solution. In the panel data case the Hausman test receives an additional functionality of checking for model misspecification between random effects and fixed effects. The null hypothesis is primarily that there is no correlation between the error term and the main independent variable [E(u|x) = 0] therefore it also suggests that a random effects model should be chosen (as it requires stricter zero conditional mean assumption holding, correlation between explanatory and error term unacceptable). The t value for the chi squared should be smaller than 0.05 to reject the H0 at an acceptable significance level and chose Fixed effects Here, The Hausmann test results are 0.00. So, the null hypothesis is rejected, and fixed effects is the preferred model.

```
Breusch-Pagan LM test of independence: chi2(171) =   525.762, Pr = 0.0000
Based on 21 complete observations over panel units
```

Now as the decision from the Hausman test suggested using the fixed effects model, the conditions of this version of multi linear regressions and of other fixed effects specific conditions have to be probed. The first test that need to be run after the Fixed Effects estimation for panels with a rather small number of groups (normally N below 20) and many years (T starting from 20)[13] is the second Breusch Pagan lagrangian multiplier test of independence. It checks for with the null hypothesis being that residuals across entities are not correlated, because often there happens to occur a problem of cross-sectional dependence in this type of macro panels. If the null hypothesis can be rejected at e.g. the 1% level the fixed effects estimation is not biased by this correlation. Here the value of 0.00 indicates exactly this on a perfect level.

[13] This condition is additional to the general Fixed Effects requirement of N<T (Wooldridge). As the present dataset is located exactly around the presented additional thresholds, the tests were run to be sure.

The second test is the Pesaran cross-sectional dependence test, which probes the estimation on any possible contemporaneous correlation within the panel (Hoechle, 2007). With the Pr value being 0.00 the hypothesis can be rejected meaning that there is no cross-sectional dependence within the panel.

```
. xtcsd, pesaran abs

Pesaran's test of cross sectional independence =     4.696, Pr = 0.0000

Average absolute value of the off-diagonal elements =     0.322
```

The fixed effects estimation assumes homoscedastic variances – meaning equally distributed across the entire panel. When not running the fixed effects estimation with robust standard errors that already takes homoscedastic variances into account, it can be tested for with the third test. This test has to be used with caution because the dataset is close to the threshold of the N<T condition and the results might therefor be too extreme – especially because it is very unlikely to have all variances being really the same (Therefore, Robustness check four probes the models with a smaller T as well; see Appendix K for the results table and Chapter 4.3 for their description) . It is a modified Wald test checking for groupwise heteroskedasticity in the fixed effects estimation. Its null hypothesis assumes homoscedasticity. This is only not to reject if the result = 0.00. meaning that there is heteroskedasticity, which is the case in the present panel. As the standard regression showed heteroskedasticity, three ways to account for it were probed. First the above-mentioned regression with robust standard errors. Afterwards a standard Fixed Effects regression was run with the natural logarithm of the dependent variable, which can account for right skewedness and thereby eliminate heteroskedasticity if it only comes from the dependent variable. Lastly, a regression with the Box-Cox transformed dependent variable was considered that can also lead to unskewed distribution. The table of estimates below shows unchanged signs and more significant values for the latter two, but the again run modified Wald test from above still indicated heteroskedasticity. Therefore, the decision was taken to stay with the robust standard error regression.

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (19)  =     205.83
Prob>chi2 =      0.0000
```

Variable	NPI_Ag_pc (y) regression with robust standard errors	Natural logarithm y	Box-Cox transformed y
PAT_TOTAL_~S	.21868549	.00065095	-9.950e-06
CO2_PBEMCAP	2.6549234	.03266509****	.00250985****
ENERGY_con~g	1.5455499	.01322689***	.00085321***
lnFERT_pc	5.653305*	.05131624****	.00349469****
Empl_Ag	.00562214	.00045589	.00005236
Ag_Land	.68507911***	.00673895****	.00047985****
AG_VA	1.8175457****	.01618568****	.00107051****
POP_den	-2.8386081***	-.02504942****	-.00164487****
lnGDPr_pc	38.048208****	.36546228****	.02524558****
_cons	-66.074462	2.7629617****	1.4713616****

legend: * p<0.1; ** p<0.05; *** p<0.01; **** p<0.001

To cope with omitted variable bias and the functional form specification, the Ramsey RESET test was conducted. In panel data, there is no such command as "ovtest" for regular multilinear regressions. For this reason, the sqared fitted values were calculated manually and then was tested to equal zero. The results suggest rejecting this hypothesis on the one per cent significance level.

```
. test sq_fit = 0

 ( 1)  sq_fit = 0

       F(  1,    18) =   23.78
            Prob > F =    0.0001
```

Lastly the condition of serial correlation needs to be checked upon in panels with large N of > 20. Serial correlation causes the standard errors of the coefficients to be smaller than they actually are and higher R-squared. Here the Wooldridge test is employed. Its null hypothesis supposes no serial correlation. The result of this regression is unable to reject this hypothesis but that would have been the desirable effect. Therefore, there is some first order autocorrelation in the panel. But due to the fact that I am handling 21 years, it is no difficulty in sight.

```
. xtserial NPI_Ag_pc PAT_TOTAL_GR_A_US CO2_PBEMCAP ENERGY_cons_ag FERT_Nitrogen Empl_Ag Ag
> _Land AG_VA CROP_out POP_den GDPreal_pc

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      18) =     12.239
           Prob > F =      0.0026
```

Most of the necessary checks have been conducted to prove Fixed Effects the right estimation method according to both the criteria of Kohler and Kreuter (2009) and Wooldridge (2015). For the missing ones indicated by named literature, the regression of Hypothesis one was run without the panel specification. The setup was then probed upon the Variance Inflation Factors. Here all values are below the necessary rule of thumb of 10. All but two are even below the sufficient rule of thumb being 4. Therefore, there is no multicollinearity in the panel (Fox, 1997, 338 as described in Kohler & Kreuter, 2009)

Variance inflation factor	VIF	1/VIF
lnGDPr pc	4.38	.23
AG VA	4.24	.24
Empl Ag	3.43	.29
Ag Land	1.87	.53
CO2 PBEMCAP	1.85	.54
POP den	1.69	.59
lnFERT pc	1.49	.67
PAT TOTAL GR A US	1.39	.72
ENERGY cons ag	1.19	.84
Mean VIF	2.39	.

Appendix I: Matrix of Correlations and Regression comparison for Hypothesis 1

Appendix I.1: Matrix of Correlation for Hypothesis 1

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NPI_Ag_pc	1.00													
(2) PAT_TOTAL_GR_A~S	0.14	1.00												
(3) ENV_PAT_tot	0.20	0.70	1.00											
(4) CO2_PBEMCAP	0.12	0.35	0.32	1.00										
(5) CO2_em_pc	0.14	0.34	0.34	0.98	1.00									
(6) ENERGY_cons_ag	0.15	-0.07	0.01	0.01	-0.01	1.00								
(7) lnFERT_pc	0.49	0.19	0.15	0.39	0.37	0.17	1.00							
(8) Empl_Ag	-0.05	-0.37	-0.26	-0.59	-0.60	0.26	-0.29	1.00						
(9) Ag_Land	-0.09	-0.27	-0.17	-0.21	-0.22	0.14	-0.14	0.38	1.00					
(10) AG_VA	-0.15	-0.36	-0.23	-0.57	-0.57	0.17	-0.46	0.77	0.36	1.00				
(11) CROP_pc	0.41	-0.05	0.04	-0.01	-0.05	0.10	0.40	0.00	0.38	-0.06	1.00			
(12) PROD_pc	0.54	0.10	0.14	0.08	0.06	0.05	0.48	-0.19	0.26	-0.22	0.90	1.00		
(13) POP_den	-0.12	0.05	-0.04	0.04	-0.00	0.13	0.11	0.29	0.49	0.14	-0.03	0.03	1.00	
(14) lnGDPr_pc	0.24	0.49	0.31	0.54	0.55	-0.17	0.46	-0.71	-0.49	-0.82	-0.02	0.22	-0.09	1.00

Appendix I.2: Regression comparison in deriving Hypothesis 1A on the ***Net Agri Production Index per capita***

Variable	**(1)**	(2)	(3)	(4)	(5)
PAT_TOTAL_~S	**.1085968**	.22045685	.26333203	.04417972	-.13997861
CO2_PBEMCAP		2.682776		7.7242856*	7.3053264**
CO2_em_pc			3.9971465**	-4.8661856**	-3.6717246***
ENERGY_cons_ag	**1.713643***	1.5700611*	1.4752726*	.99532245	.6897199
GPAT_envtech	**.0598401**	-.01842266	-.10331831	-.27486266	-.38882812
lnFERT_Nit	**6.483145*** **	5.5192815**	4.9130999*	3.1576676	1.1679289
Empl_Ag	**.1285712**	-.00220745	- .08824488	.04896166	.14860906
Ag_Land	**.7424741*** **	.6895165***	.65712746**	.58518115**	.58084307***
AG_VA	**1.80171********	1.8244686****	1.7935585****	1.3421747**	.97211787**
CROP_pc				140.62786**	
PROD_pc					48.960911****
POP_den	**-2.766214*** **	-2.9168946***	-3.0209407****	-2.3716655***	-1.9152541**
lnGDPr_pc	**41.11183********	38.335752****	35.694031****	33.978262****	30.171198***
_cons	**-188.2611**	-148.6204	-112.90973	-129.70574	-112.6331

legend: *p<0.1 ** p<0.05; *** p<0.01; **** p<0.001

Explanations I.2: Developing the control variables for hypothesis one, different control s had to be tested. Regression 1 is the base with the least included ones. Its shows mostly significant results (2) works with Production-based CO2 emission per capita that are measured in tonnes as intensity in realtion to energy production. (3) calculates plain co2 emissions per capita non ag related in the country as an indicator of industrialisation- Here the positive influence on productivity is significant on the 10% level. Regressions 4 and 5 add more productivity variables but due to a high correlation they will not be used. In general signs as size of the coefficients stayed very similar thus including different other control variables. There is no sign of overdispersion with all varibales included.

Appendix I.3: Regression comparison in deriving Hypothesis 1B on the ***Net Agri Production Index per capita***

Variable	(6)	**(7)**	(8)	(9)	(10)
ENV_PAT_tot	1.509362	**1.9456723****			
ENV_PAT_GOODS					8.9136958
GPAT_pmn			-.10016942	-.06534025	
CO2_PBEMCAP		**2.488971**		2.3019022	2.5470164
ENERGY_cons_ag	1.6476391*	**1.5149807**	1.6763537*	1.5959702	1.5743552*
GPAT_envtech	.04125706	**-.02644085**	.1687156	.07428641	-.01560614
lnFERT_pc	6.2665539**	**5.4803681****	6.0132784**	5.325346*	5.5391941**
Empl_Ag	.14366526	**.01456753**	.05762495	-.04876004	-.00211127
Ag_Land	.74448605**	**.69445993****	.72141538***	.68801934***	.69306387***
AG_VA	1.7578397****	**1.7871818******	1.8661702****	1.884142****	1.827239****
POP_den	-2.7867185***	**-2.8353125*****	-2.7136414***	-2.8402761***	-2.8246561***
lnGDPr_pc	40.213656****	**37.842901******	43.64308****	41.044944****	38.820232****
_cons	-175.21091	**-64.582778**	-208.46507	-175.08756	-74.65088

legend: * p<0.1; ** p<0.05; *** p<0.01; **** p<0.001

<u>Explanations I.3:</u> In regression six the very basic setup from Hypothesis 1A is tested but adding the content wise reasonable CO_2 emissions in regression (7) when probing for environmental effects in this hypothesis also delivers better results. To be sure that this is already the optimal result for H1B, the other OECD Green Patent classification that combines other not primarily climate change mitigation techniques with agricultural context, in addition to be the weaker variable form the context side also delivers weaker results (8 & 9). Final assurance is reached a comparison of estimates with the other already lagged environmental patent variable on CCM-Tech goods (10), but as its main independent variable coefficient was less significant I stayed with the variable derived from literature. All regressions are run with robust standard errors.

Appendix J: Matrix of Correlations and Regression comparison for Hypothesis 2

Appendix J.1: Matrix of Correlation for Hypothesis 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) NPI_Ag_pc	1.00										
(2) PAT_A01tot_GR_~S	-0.00	1.00									
(3) PAT_A01C_GR_A_US	0.01	0.18	1.00								
(4) ENERGY_cons_ag	0.15	-0.00	-0.05	1.00							
(5) GPAT_envtech	-0.04	-0.04	-0.01	0.06	1.00						
(6) lnFERT_pc	**0.49**	0.14	0.01	0.17	-0.06	1.00					
(7) Empl_Ag	-0.05	-0.21	-0.08	0.26	-0.01	-0.29	1.00				
(8) Ag_Land	-0.09	-0.05	-0.02	0.14	0.11	-0.14	0.38	1.00			
(9) AG_VA	-0.15	-0.19	-0.05	0.17	-0.05	**-0.46**	0.77	0.36	1.00		
(10) POP_den	-0.12	0.09	0.06	0.13	-0.00	0.11	0.29	**0.49**	0.14	1.00	
(11) lnGDPr_pc	0.24	0.23	0.09	-0.17	-0.02	0.46	-0.71	**-0.49**	**-0.82**	-0.09	1.00

Appendix J.2: Regression comparison in deriving Hypothesis 2 on the ***Net Agri Production Index per capita***

Variable	**(1) fe_2_a like H1B**	(2) fe_2_b without logs	(3) fe_2_c including other CO2 Emissions	(4) fe_2_d including crop output
PAT_A01tot~S	**-3.9653515**	-3.7017613	-.72682935	-3.9653515
PAT_A01C_G~S	**22.016422**	34.435027	22.880477	22.016422
CO2_PBEMCAP	**2.4673338***	4.6305788**		2.4673338
CO2_em_pc			3.8520866**	
ENERGY_con~g	**1.6126977**	.98318444	1.5224044*	1.6126977*
GPAT_envtech	**.00055125**	-.1592398	-.0792599	.00055125
FERT_pc		473.44537**		
lnFERT_pc	**5.7064532****		5.0784618*	5.7064532**
Empl_Ag	**-.01927016**	-.28319099	-.11133728	-.01927016
Ag_Land	**.69736292*****	.72261923**	.66677543**	.69736292***
CROP_pc				124.8549*
AG_VA	**1.8476562******	.86581846**	1.8228487****	1.8476562****
POP_den	**-2.7910367*****	-2.8659738**	-2.9054216****	-2.7910367***
GDPreal_pc		0.00170866**		
lnGDPr_pc	**39.246569******		36.730478****	39.246569****
_cons	**-80.216834**	239.6743*	-54.694533	-80.216834

legend: * p<0.1; ** p<0.05; *** p<0.01; **** p<0.001

Explanation J.2: To proof the right selection of control variables to be in place also for the new relationship of agricultural patents, four regression were run. The first took the same controls as in hypothesis 1 (1). This should secure a high level of consistency across the models and make the results better comparable. In (2), the natural logarithms of *Nitrogen Fertiliser* and *real GDP* were removed. This made the coefficients more difficult to interpret and the significances weaker but did not change any major relationship. In (3) the *production-based* CO_2 *emissions per capita* were again replaced by general population-wide CO_2 *emission per capita* not yielding any better results. Therefore, the consistent way was kept. Lastly, in (4) the higher correlated crop output per area variable was included but it did not yield any positive changes. Finally (1) was kept as the most consistent way of regression for Hypothesis 2.

Appendix K: Robustness Checks for Hypotheses 1 and 2

VARIABLES	(1) H1A – STD	(2) H1B – STD	(3) H2A – STD	(4) H2B – STD	(5) H1A – SQA	(6) H1B – SQA	(7) H2A – SQA	(8) H2B – SQA
std_PAT_TOTAL_GR_A_US	0.0414				0.159			
	(0.0941)				(0.790)			
c.PAT_TOTAL_GR_A_US #c.PAT_TOTAL_GR_A_US					0.00307			
					(0.0447)			
std_ENV_PAT_tot		0.0806**				1.822		
		(0.0381)				(3.017)		
c.ENV_PAT_tot #c.ENV_PAT_tot						0.0198		
						(0.350)		
std_PAT_A01tot_GR_A_US			-0.0110				-8.498	
			(0.0272)				(29.64)	
c.PAT_A01tot_GR_A_US #c.PAT_A01tot_GR_A_US							14.82	
							(63.86)	
std_PAT_A01C_GR_A_US				0.0103				12.45
				(0.0104)				(153.9)
c.PAT_A01C_GR_A_US #c.PAT_A01C_GR_A_US								35.15

VARIABLES	(1) H1A – STD	(2) H1B – STD	(3) H2A – STD	(4) H2B – STD	(5) H1A – SQA	(6) H1B – SQA	(7) H2A – SQA	(8) H2B – SQA
(std_)CO2_PBEMCAP	0.395	0.370	0.364	0.374	2.638	2.463	2.412	2.513
	(0.265)	(0.272)	(0.260)	(0.264)	(1.805)	(1.904)	(1.740)	(1.752)
(std_)ENERGY_cons_ag	0.171	0.168	0.178*	0.178	1.546	1.513	1.617*	1.604
	(0.100)	(0.102)	(0.103)	(0.103)	(0.907)	(0.919)	(0.914)	(0.932)
(std_)lnFERT_pc	0.329**	0.319**	0.331**	0.331**	5.660**	5.493**	5.703**	5.692**
	(0.142)	(0.143)	(0.143)	(0.143)	(2.469)	(2.551)	(2.464)	(2.454)
(std_)Empl_Ag	0.00357	0.00877	-0.0108	-0.0109	0.00335	0.0141	-0.0169	-0.0169
	(0.264)	(0.265)	(0.264)	(0.264)	(0.412)	(0.419)	(0.419)	(0.415)
(std_)Ag_Land	0.561***	0.568***	0.570***	0.571***	0.685***	0.694***	0.694***	0.697***
	(0.191)	(0.195)	(0.188)	(0.190)	(0.231)	(0.239)	(0.234)	(0.232)
(std_)AG_VA	0.691***	0.680***	0.704***	0.701***	1.821***	1.790***	1.856***	1.844***
	(0.161)	(0.155)	(0.156)	(0.156)	(0.407)	(0.409)	(0.425)	(0.411)
(std_)POP_den	-4.655***	-4.650***	-4.569***	-4.593***	-2.841***	-2.833***	-2.785***	-2.800***
	(1.339)	(1.328)	(1.300)	(1.307)	(0.812)	(0.827)	(0.794)	(0.798)
(std_)lnGDPr_pc	1.231***	1.225***	1.274***	1.266***	38.12***	37.89***	39.49***	39.12***
	(0.303)	(0.292)	(0.279)	(0.286)	(9.371)	(9.170)	(8.568)	(8.837)
Constant	8.19e-09***	7.74e-09**	7.86e-09***	7.85e-09***	-66.39	-65.06	-82.69	-78.60
	(2.84e-09)	(2.69e-09)	(2.63e-09)	(2.69e-09)	(139.5)	(137.3)	(130.8)	(133.5)
Observations	399	399	399	399	399	399	399	399
R-squared	0.599	0.604	0.598	0.598	0.599	0.604	0.598	0.598
Number of Country_code (N)	19	19	19	19	19	19	19	19

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