The spiky world of innovation at science parks

A research about the influence of science parks in the Netherlands on the levels of patenting within municipalities and neighbouring municipalities in the years 1980-2020

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Abstract

This research is about the impact of science parks in the Netherlands on innovation within municipalities and neighbouring municipalities. Science parks are geographically bounded places that seek to facilitate collaboration between businesses, universities, higher education institutes and research organisations with innovation as the main goal. There is a high activity of innovation at science parks, which pulls the interest of policy makers to form such parks in order to stimulate the innovation within the region. While innovation is sticky, knowledge can travel through space with some aspects making the transfer of knowledge easier for instance, via face-to-face contacts or having the same type of technology. These knowledge spillovers can contribute to the process that the region benefits from the existence of a science park in terms of innovation. This research tries to unfold the relation by looking at the number of science parks in a municipality, the type of science park and if geographic proximity to a science park plays a role in the levels of patenting within a municipality and neighbouring municipalities.

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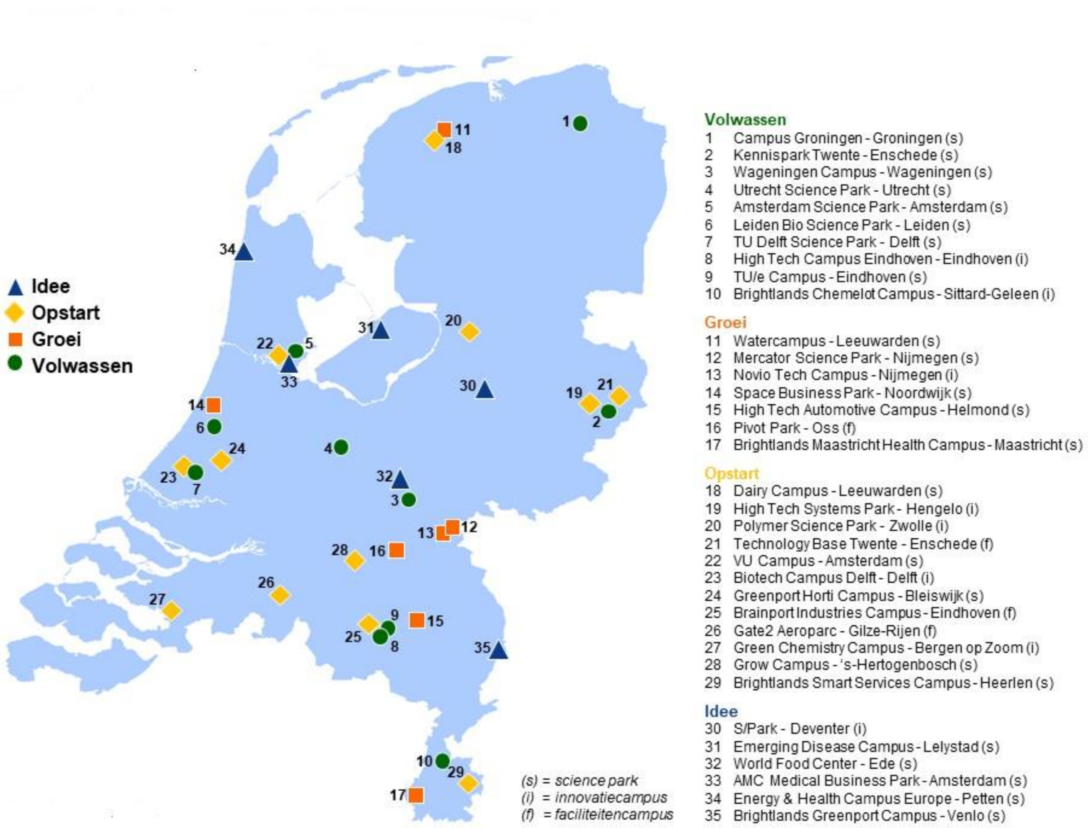
1. Introduction

Science parks are relatively new concepts as the first science park, Silicon Valley, arose in the 1950's (UNESCO, 2017). Around the world, science parks are being established and promoted as property developments aimed at supporting research-based commercial activity. Science parks are geographically bounded places that seek to facilitate collaboration between businesses, universities, higher education institutes and research organisations with innovation as the main goal (le Duc and Lindeque, 2017). A science park is a magnet, breeding place and showpiece for the city where it creeps of talented people. A science park offers job opportunities, and when the economy grows, jobs at campuses and science parks increase even more (Bruinenberg, 2018). Besides, it also has a positive influence on the employment opportunities in the municipality as more institutes and companies locate in the city. While the world is globalising, innovation is stickier than ever. As there is a high activity of innovation at science parks, municipalities try to form such parks in order to stimulate innovation in the region. Innovation can lead to economic growth and is seen as a way of creating a new process (Schot and Steinmueller, 2018).

The Netherlands hosts tens of campuses and science parks spread throughout the country. Buck Consultants International (BCI) (2018) mapped the campuses in the Netherlands and divided the types of campuses in three groups: a science park, an innovation campus and a facility campus. According to BCI (2018), there are eight science parks in the 'adult' phase in the Netherlands, based on the attractiveness for businesses.

Figure 1: Overview of 35 campuses in the Netherlands according to their development stage



Source: BCI, 2018

However, the exact outcomes of a science park in relation with the innovative output has not been researched yet. There is no clear evidence that science parks contribute to the innovation within a municipality, let alone that the region can benefit from it. While innovation is sticky, the transfer of knowledge through space is possible via the so-called knowledge spillovers. Knowledge spillovers are intellectual gains gathered via an exchange of information for which no direct compensation to the producer of the knowledge is given, or for which less compensation is given than worth the value of the knowledge (Feldman and Kogler, 2010). Where innovation is, are knowledge spillovers, but knowledge spillover are not a self- reinforcing process. Some aspects make the transfer of knowledge through space easier for instance, via face-to-face contacts or having the same type of technology. These knowledge spillovers can contribute to the process that the region benefits from the existence of a science park in terms of innovation.
So, a lot of research has been done about the contribution of a cluster, such as a science park, to the municipality, but not exactly, what having a science park does with the innovation within the municipality and with the region. The purpose of this research is to provide insights into the role of science parks on the level of innovation in a municipality, and the level of innovation on the neighbouring municipalities. The research question is as follows:

To what extent do science parks in the Netherlands influence innovation within municipalities and neighbouring municipalities

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1.1 Relevance of the research

With this research question the research is, on the one hand, scientifically relevant as it captures the gap in the scientific literature about the relation between a science park and innovation within a municipality and neighbouring municipalities. While Bruinenberg (2018), states that innovation is important for economic growth and development, it has not been proved that municipalities achieve greater innovation by hosting a science park. Therefore, it is important to research the exact relation between science parks and innovation within a municipality. A second aspect of this research dives into the spatial effect of science parks and to what extent firms in neighbouring municipalities can benefit of the knowledge spillovers because of the proximity to a science park. As science parks seek to facilitate collaborative innovation between businesses, universities, higher education institutes and research organisations to the benefit of all participating organisations, there is a concentration of innovative activity (le Duc and Lindeque, 2017). While knowledge tends to be localised, face-to-face interactions, collaborations and networks among firms and individuals contribute to the diffusion of new ideas. Because of these knowledge spillovers, areas spatially close to municipalities hosting science parks may benefit as well, since firms may learn from one another. This poses the question of whether and to what extent the proximity of a science park contributes to innovation in neighbouring municipalities. While Magionni, Nosvelli and Uberti (2007) researched the impact of clusters on spatial knowledge spillovers, the relation between the existence of a science park on the level of innovation within and outside the municipality has not been researched yet.

On the other hand, there is also a societal relevance of this research. The purpose is to provide policy implications for municipalities if science parks are a way to success for innovation and how they can boost the region as a whole. Of all economic activities, it is innovation that benefits the most from location. As scholars state that the world became flat due to globalisation, innovation within places is spikier than ever as it concentrates in just few places in the world (Feldman and Kogler, 2010). Within a cluster, there is a certain ‘buzz’ where corporations can benefit from. Iammarino and McCann

(2015), describe that policy-makers want to set up such knowledge intensive clusters, such as science parks, in order to boost innovation and enable participation in the global knowledge economy. With a science park, a region is put on a global map of innovative places, which, in result, would turn out in economic growth as more and more companies are allocated at the science park. However, this research points out if a science park is indeed the key to success in making a region innovative. This research provides insight into which type of science park e.g. science (business) park, campus or innovation district, is the most beneficial for a region or if there are other factors that influence innovation. With this knowledge, municipalities can adjust its policy in order to create the most beneficial environment for innovation and maybe reconsider if setting up a science park is enough.

1.2 Structure

This research starts with a theoretical framework where the most relevant concepts of geography and innovation and science parks are being discussed. Second, comes the methodology, which describes how the research is done and gives an introduction in the case of science parks in the Netherlands. As third comes the analyses, which are divided, into two chapters. Chapter 4 discusses the relation between the number of science parks and type of science parks on innovation within municipalities from 1980-2020. The analysis starts with discussing patterns in three maps; 1980, 2000 and 2018, followed by a regression. Chapter 5 dives into the relation between the number of science parks and the types of science parks on innovation in neighbouring municipalities in only 2018. The analysis starts with looking at the patterns in a map about science parks and patenting data, followed by a regression of 2018 and a spatial regression with three different models. After chapter 4 and 5 the hypothesis are answered and the findings are being summed in the conclusion. The research ends with a discussion of the findings, how this relates to the already existing literature and how it can contribute to future research.

2. Theoretical framework

Science parks are relatively new concepts as the first science park, Silicon Valley, arose in the 1950's (UNESCO, 2017). In the Netherlands, the most science parks were established in the beginning of the 21st century, while the theory of clustering dates back to 1920. There are more concepts at play within a science park. It all can be traced back to the Geography of Innovation, and how innovation spills over through space. As innovation is locally bounded, clusters arise too. The first theories of cluster formation focuses, on the one hand on the theory of agglomeration economies and on the other hand on the spinoff dynamics. The second concept is a counterpart of the first one, and is about the proximity theory that declares it is not only about geographical proximity but also different types of proximity that influence innovation. Clusters are highly innovative places which result into a high level of knowledge spillovers. On the one hand, knowledge spillovers are geographically bounded, but on the other hand, there are ways for knowledge to travel through space. All these different theoretical places are intertwined and come at play at places like science parks.

2.1 Geography of Innovation

Combining different types of knowledge to produce something new, different and unprecedented that has economic value, is a way to create something innovative (Feldman and Kogler, 2010). Innovation is not a new concept, as in the 70s scholars and policy makers were interested in innovation because it results in economic growth (Schot and Steinmueller, 2018). Innovation was seen as a way for creating a new process. In the 90s, there was a shift of thinking in the innovation discourse. The interest came for 'open innovation 'as relational data and networks of collaborations also could take place within systems. Policy was framed to push more collaborations with the goal to boost innovation. In the 2010s, innovation shifted from a goal to a means that has the purpose to achieve a goal (Schot and Steinmueller, 2018). Thereby, the goals were about not only economic growth anymore, but also more about for instance, sustainability. As this is the newest way of thinking about innovation, it is not yet a dominant approach.
What played an important role in the evolution of innovation, was the start of a connected world in the 70s due to communications development and faster infrastructure. Everything could happen anywhere and economic activities are not locally bounded anymore. Scholars say that the world became flat as opportunities were uniformly distributed. Global outsourcing allows firms to lower production costs, which is not the case for technologically sophisticated firms as they compete on the basis of differentiated performance and innovation (Feldman and Kogler, 2010). The production of the goods that technological firms make, can still be outsourced, but the highest value activity, innovation, is typically focused in certain locations. While scholars say that the world became flat, innovation theorists state that the world even became spikier than ever. Feldman (1994) saw the importance of why location matters for innovative activity, and even that of all economic activities, innovation benefits the most from location. The more relative importance of new economic knowledge in the industry, the more the location of knowledge production is geographically concentrated (Audretsch and Feldman, 1996). The breeding places for new economic knowledge are industry R&D, university R&D, and skilled labour. The stickiness of innovation has to do with the type of knowledge. Tacit knowledge is harder to acquire through the market than codified knowledge. However, proximity plays an important role in the diffusion of tacit knowledge. The transfer of tacit knowledge may need greater spatial proximity than codified knowledge (le Duc and Lindeque, 2017). Moreover, location matters most at the earliest stage of the industry life cycle, which indicates a link between the localization of innovation and the maturity level of particular industries within a cluster (Feldman and Kogler, 2010). Clusters have a certain 'buzz' where corporations can benefit from. Knowledge is in the air and the advantages that arise from proximity, such as the reduce of costs, are all reasons why companies are pulled to cluster.

2.2. The formation of clusters

The first theory comes from the scientist Marshall and states that companies cluster together because of agglomeration economies (Marshall, 2013). Localisation economies is about the advantages to firms in the same industry when located together in the same region, while they do not have these advantages outside the region. Such a region can be determined by the natural resources available or a close location to specialized facilities for example a harbour, while also economic factors can play a role, named Marshallian externalities. It is beneficial for companies to locate to local specialized labour markets or close to the market of specialized suppliers and buyers. Another reason for clustering can be related to the principle of 'knowledge in the air' at which companies benefit from the local knowledge spillovers. The spatial clustering of an industry has positive effect on all firms that belong to that industry, while exiting a cluster has a negative effect on firms. According to Marshall (2013), the negative effects of leaving the cluster against the positive effects for all new firms entering, are the reason why clusters exist and persist over time.

For many decades, there seemed to be consensus about the theory of agglomeration economies until a second theory, namely spinoff dynamics, came up. The agglomeration theory could not explain cluster formations that are not related to any natural or economic externalities. Arthur was the initiator of this theory of clustering where spinoffs are a particular type of entry leading to a clustering of an industry. Each entrant in a new industry is a spinoff of the incumbent firm and locates near their parent organization. This entails a self-reinforcing and path-dependent process, which is not determined by localization economies, as stated by Marshall. A location of a new industry is unpredictable and can happen everywhere caused by small events. Klepper (2007) expands the idea of the spinoff dynamics and states that spatial clustering of an industry is caused by local entry of spinoff that originate from successful parents and therefore show lower exit rates. The survival model within Klepper's theory of spinoff dynamics highlights the importance of the success of the parent firm. The disagreements within a firm that occurs, can lead to shakeouts when the disagreement is large enough to overcome the cost of starting a new firm. The new firm has inherent routines from parents firms, and tend to locate near the incumbents (Klepper, 2007). Successful parents generate more successful spinoffs that leads into a build-up of superior firms around successful early entrants. Klepper (2010) adds that better firms not only spawned more and better spinoffs, but firms in more closely related industries were more likely to diversify into both industries and perform better than other entrants. Consequently, regions with superior firms will expand their total output, contributing to an agglomeration of economic activity, without any links to conventional agglomeration economies that benefit all co-located firms, as stated by Marhsall (2013). According to Klepper (2007), the spatial concentration of an industry is thus caused by the accidental presence of very successful spinoffs.

However, the theories of the agglomeration economies and the spinoff dynamics do not exclude one another. Organizational and heredity seem to have a major influence on the emergence and growth of clusters, but it is less clear whether traditional agglomeration economies related to labour pooling, proximity to suppliers and buyers, and localized knowledge spillovers played a similar role (Klepper, 2010). Agglomeration economies might have played a role in the entry of firms to the cluster by enhancing the profitability, and hence probability of entry of indigenous potential entrants. Evidence shows that if the agglomeration economies were at play, all kind of firms would have been superior performers in the cluster, which is not the case in the research of Klepper (2010). The superiority of firms within a cluster were largely restricted to spinoffs, and in particular, spinoffs descended from the leaders that entered at the largest size. Perhaps there could be an equilibrating process at play in a cluster, such as bidding up of wages and prices that offset the benefits of agglomeration economies and limited the performance of non-spinoff entrants in the clusters. If such a process was operative it would have to be explained why it did not compete away the advantages realized by the spinoff in the clusters (Klepper, 2010). It is thus still unclear what the exact effects are of agglomeration economies in the formation of clustering originating from successful spinoffs.

2.3 Proximity as another theory of 'clustering'

Besides the theory of agglomeration and spinoff theory, the proximity theory questions the role of geographical proximity and the local buzz. This theory acknowledges the role of networks in innovation process and not just the innovation that occurs because of co-location (Boschma, 2005). Besides the role of geographic proximity in the innovation process, there is also an importance of the different types of proximity (such as cognitive and organizational dimensions) that are beneficial for companies in their interactive learning and innovation. Besides that, Boschma (2005) also investigates the negative impacts on innovation when there is too much proximity. In this paper, there are five dimensions of proximity discussed: cognitive, organizational, social, institutional and geographical proximity.

Cognitive proximity

As a rule, firms search in close proximity to their existing knowledge base, which provides opportunities and sets constraints for further improvement when working with companies closely related to your knowledge base (Boschma, 2005). Cognitive proximity mostly is relevant for companies with a high degree of tacit knowledge. Thereby, the positive effect for firms is much higher when engaging in more radical, exploratory alliances, than in more exploitative alliances (Nooteboom et al., 2007). It is important that the cognitive distance is not too great in order to maintain the capacity of actors or firms to absorb new knowledge. Namely, too much cognitive proximity can be detrimental to learning and innovation. Besides that, it also increases the risk of lock-in, it limits the absorptive capacity of firms, and the problem of undesirable spillovers to competitors (Boschma, 2005). While, too much cognitive distance can lead to problems of communication. Important to be aware of when cooperating with others, is the trade-off to be made between the opportunity of novelty value and the risk of misunderstanding (Nooteboom et al., 2007). When alliances are driven by the goal to benefit from a rise in novelty value when cognitive distance increases, it ignores the notion that employing such strategies comes at a risk of decreasing understanding, which affects the innovation performance negatively. In order to prevent too much or too little cognitive distance, a geographical cluster endowed with a common knowledge base made up of diverse, but complementary, knowledge resources can be the solution. Nooteboom et al. (2007), state that innovation performance is a parabolic, inverted-U shaped function of technological distance between alliance partners. Essential for interactive learning, is an absorptive capacity that is open to new ideas (Boschma, 2005).

Organizational proximity

According to Messini Petruzzeli (2008) it is cognitive proximity and organizational proximity together that drives collaboration. "Organizational proximity refers to the set of interdependencies within as well as between organizations 'connected by a relationship of either economic or financial dependence/interdependence (between member companies of an industrial or financial group, or within a network)" (Boschma, 2005, pg. 65). In organizational proximity, partners find the relevant organizational similarities that help them to work together, which is relevant when it comes to interactive learning (Messini Petruzzeli, 2008). As discussed, a common knowledge and competence base is a prerequisite for bringing firms together, but knowledge creation also depends on a capacity to coordinate the exchange of complementary pieces of knowledge owned by a variety of actors within and between organizations (Boschma, 2005). Organizations can be seen as vehicles that enable the transfer and exchange of information and knowledge. However, too much organizational proximity can lead to a lack of flexibility and lock-in, while too little organizational proximity goes along with a lack of control, which increases the danger of opportunism. The solution for this is a loosely coupled system that reflects a level of organizational proximity in which both control and flexibility are guaranteed. In such a governance structure, there is room for a satisfactory cognitive level, implying that organizational and cognitive proximity are complement to one another.

Social proximity
Besides cognitive and organizational proximity, Werker, Ooms and Caniëls (2016) point out that social proximity has an important role in collaborations as well. Social proximity is about embedded relations between agents at the micro-level. A relation is socially embedded when they involve trust based on friendship, kindship and experience. For an organization to learn and innovate some social proximity is needed. One of the main reasons is that trust-based social relationships facilitate the exchange of tacit knowledge, which is harder to communicate, and to trade through markets (Boschma, 2005). However, on the one hand, too much social proximity can lead to lock-in and underestimated risks of opportunism due to loyalty. On the other hand, too little social proximity can be harmful because of the lack of trust and commitment between agents. The social proximity can be seen as a U-relationship wherein the more embedded economic relationships, the better the economic performance of a firm up to a certain threshold, after which adverse impacts arise because of lock-in (Boschma, 2005). To guarantee an effective level of social proximity, a network should consist of both market relationship, the arm's-length ties, and the embedded relationships. Geographical proximity plays a certain role in the social proximity, as short geographical distance favour social interaction and trust building.

Institutional proximity
Where social proximity has been defined in terms of socially embedded relations between agents at the micro-level, institutional proximity is about the institutional framework at the macro-level (Boschma, 2005). Institutions are enabling or constraining mechanisms that affect the level of knowledge transfer, interactive learning which is important for innovation. Institutional proximity includes both the idea of economic actors sharing the same institutional rules of the game, as well as a set of cultural habits and values (Boschma, 2005). Important is to keep a certain distance of institutional proximity as too much proximity is unfavourable for new ideas and innovation due to lock in, because of obstructing awareness of new possibly, and inertia, which hinders the required institutional readjustments. Again, too little institutional proximity is also not beneficial, due to weak formal institutions and a lack of social cohesion and common values (Boschma, 2005). An effective institutional structure needs to balance between institutional stability, openness and flexibility. The system should set several requirements that guarantee these checks and balances.

Geographical proximity
Geographical proximity refers to the spatial or physical distance between economic actors, both in absolute and relative meaning (Boschma, 2005). Short distances bring people together, favour information contracts and facilitate the exchange of tacit knowledge. The larger the distance, the less intensity of these positive externalities, and the more difficult it gets to transfer tacit knowledge. As discussed in the section about the spinoff theory and the agglomeration theory, is that firms within a cluster have a better innovative performance than firms outside this cluster. In the proximity theory, geographical proximity, in combination with some level of cognitive proximity, is sufficient for innovation, but other forms of proximity may also act as a substitute for geographical proximity. Geographical proximity facilitates the interaction and cooperation, while it is not necessarily needed for interactive learning and innovation. Singh (2005) states that geographical proximity is especially important in the establishment of interdisciplinary research collaboration (when cognitive proximity

is low), while inventors working in the same field collaborate on average over longer geographical distances. So, when it comes to the exchange of tacit knowledge, face-to-face contacts are essential, as tacit knowledge is hard to spillover via space (Boschma and Frenken, 2010). Ponds, van Oort and Frenken (2007) found that geographical proximity is especially important in the establishment of university-industry-government relationships e.g. triple Helix. In these relationships, the institutional proximity is low, so it needs the support of geographic proximity in order to make the relationship work. Geographic proximity is thus less important in university-university collaboration where actors operate under the same institutions. Agrawal, Cockburn and McHale (2006), found that knowledge can be transferred between firms in different locations when there are employees that are socially linked because of a shared past. Ooms, Werker and Caniëls (2018) add to this that there is a role of personal proximity in the forming of collaborations as partners who are personally close, like each other, and therefore enjoy working together. It is social proximity and personal proximity that act as the glue of collaborations, and not geographical proximity (Ooms, Werker and Caniëls, 2018).
Still, institutional, social and organizational proximity are important for the process of interactive learning and innovation, but geographical proximity may facilitate the process of innovation and interactive learning. Geographical proximity can thus be seen as a catalyst for innovation but is not necessarily needed:

"In other words, social networks are not necessarily localized geographically, because there is nothing inherently spatial about networks. This is not to deny that social networks can be location specific, sustained and reproduced by ongoing collective action of local actors. In that case, the resulting knowledge spillovers will be geographically localized as well, and geographical proximity becomes a necessity for being a member of a network" (Boschma, 2005, pg. 69)

To conclude, effective learning and innovation require an absorptive capacity open to new ideas (cognitive proximity), while they necessitate mechanisms of coordination and control that are flexible and focused on the outside (organizational, social, institutional and geographical proximity) (Boschma, 2005). Within all these forms of proximity, it is important to find a balance as too much or too little proximity is not beneficial for the interactive learning and innovation (figure 2).

Figure 2: Overview of the five forms of proximity

	Key dimension	Too little proximity	Too much proximity	Possible solutions
1. Cognitive	Knowledge gap	Misunderstanding	Lack of sources of novelty	Common knowledge base with diverse but complementary capabilities
2. Organizational	Control	Opportunism	Bureaucracy	Loosely coupled system
3. Social	Trust (based on social relations)	Opportunism	No economic rationale	Mixture of embedded and market relations
4. Institutional	Trust (based on common institutions)	Opportunism	Lock-in and inertia	Institutional checks and balances
5. Geographical	Distance	No spatial externalities	Lack of geographical openness	Mix of local 'buzz' and extra-local linkages

Source: Boschma, 2005.

2.4 Science parks as a type of cluster

Science parks are an example of a cluster formation and a network as science parks seek to facilitate collaborative innovation between businesses, universities, higher education institutes and research organisations to the benefit of all participating organisations (le Duc and Lindeque, 2017). A science park is an organisation managed by specialised professional, with the support of policy interventions and subsidies, whose main aim is to increase the wealth of its community by promoting the culture of innovation and the competitiveness of its associated businesses and knowledge-based institutions (le Duc and Lindeque, 2017). It is a business park that is related to a university where R&D takes place through universities, academic centres, research institutes and companies, and is thus less focused on business growth. Science parks differ in their specialisation from bio-medical drug development to subatomic physics and ICT. These type of clusters are attractive places for big and small companies due to the benefits of regular interaction, enabled by being located physically closely, for knowledge-intensive activities. A science park is an example of a competence-based social network. In this network, high technological opportunities come primarily from sources such as university academic research (Iammarino and McCann, 2015). In this technological environment, the type of knowledge tends to be both generic and non-systemic, with high rates of market entry and exit, a strong degree of volatility of market shares, and low levels of market concentration. The tacit and sticky nature of knowledge requires geographical proximity. At science parks, there is a 'leaky' environment of new knowledge that enables the high potential for spillovers (Iammarino and McCann, 2015). Firms that depend on innovation and technological change will co-locate in a science park that ensures the best possible knowledge externalities and spillovers. Firms may establish a physical presence in a science park in a variety of modes, from small representative offices to larger R&D departments (le Duc and Lindeque, 2017).

Besides the science park, there are two types of clusters that are in the vernacular labelled as a science park, but substantially differ: a campus and innovation district.
A campus is a business site where one or more corporate anchor tenants are focused on R&D. Interaction and cooperation on the research area is actively stimulated on the campus (BCI, 2018). It consists of a large surface site area in terms of square meters, with mainly multiple building locations, and space for more than 100 resident organisations (Ng et al., 2019). The difference between a science park and a campus is that at a science park the focus relies on the collaboration between knowledge institutions, companies and government, also known as Triple Helix, whereas at a campus the focus is on the businesses. A campus can have a knowledge institution but it is not a requirement for labelling such sites as a campus. A science park and a campus are not opposites, but are in line with each other differentiated by the focus of the collaboration.
However, the innovation district does have total different features than the science park and campus. An innovation district is an innovative location where the pull factors do not come from a knowledge institution or a business (e.g. university, university medical centre, research institute and a R&D centre from a big international company) as for the science park and campus, but from specific research facilities and pilot plans (BCI, 2018). The facilities are supportive for businesses that can use them in collaboration with other companies. As the facilities are mainly focused on business support, the aim of an innovation district is also to help start-ups in growing their business (Ng et al., 2019).

All the typologies of a science park are geographically bounded and are breeding grounds for innovation. Important to note is that in the Netherlands when people talk about a campus, they refer to a science park or one of the other two types. In foreign countries, a campus can also be associated with a university campus or a corporate campus with just several companies clustering together.

2.5 The spatial spillover effect

Since networks are defined and demarcated in a non-territorial way, knowledge spillovers are also not spatially bounded, while clusters are (Boschma, 2005). Knowledge spillovers are intellectual gains gathered via an exchange of information for which no direct compensation to the producer of the knowledge is given, or for which less compensation is given than worth the value of the knowledge

(Feldman and Kogler, 2010). Besides the stickiness of innovation, knowledge spillovers also rather tend to cluster at places where R&D facilities and skilled labour are important. Where innovation occurs, knowledge spillovers are being produced too. In the scientific literature, there are two camps in the discussion about spatial spillovers.

One side of the scholars state that knowledge is sticky and hard to spillover. The main argument is related to the type of knowledge as for tacit knowledge it is more complex to diffuse than codified knowledge. Tacit knowledge, is spatially sticky, difficult to create and thus harder to spillover to the region outside of its production (Balland and Rigby, 2016). What makes the knowledge complex is unclear. The spillovers of complex knowledge are relatively immobile and stay embedded in the workers, firms and institutions of particular places. Whilst, low complexity, more routinized forms of knowledge are easier to move over space and thus easier to spillover to regions that are not geographically close to where the knowledge is produced, Balland and Rigby (2016) suggest that complex knowledge is not impossible to diffuse. Tacit knowledge can diffuse via personal contacts and face-to-face interaction, but in order to get face-to-face interaction and personal contacts geographic proximity plays a role in the level of spillovers. Cities are key examples of such places of knowledge exchange, and in addition, they are places of creativity, dense locations of knowledge production and spillovers (Feldman and Kogler, 2010). Research points out that the higher the density, the higher the level of knowledge spillovers. However, innovation is seen as a 'local public good' which benefits scientist within the region or its neighbourhoods, but it fades farther away as contacts and interaction decreases.

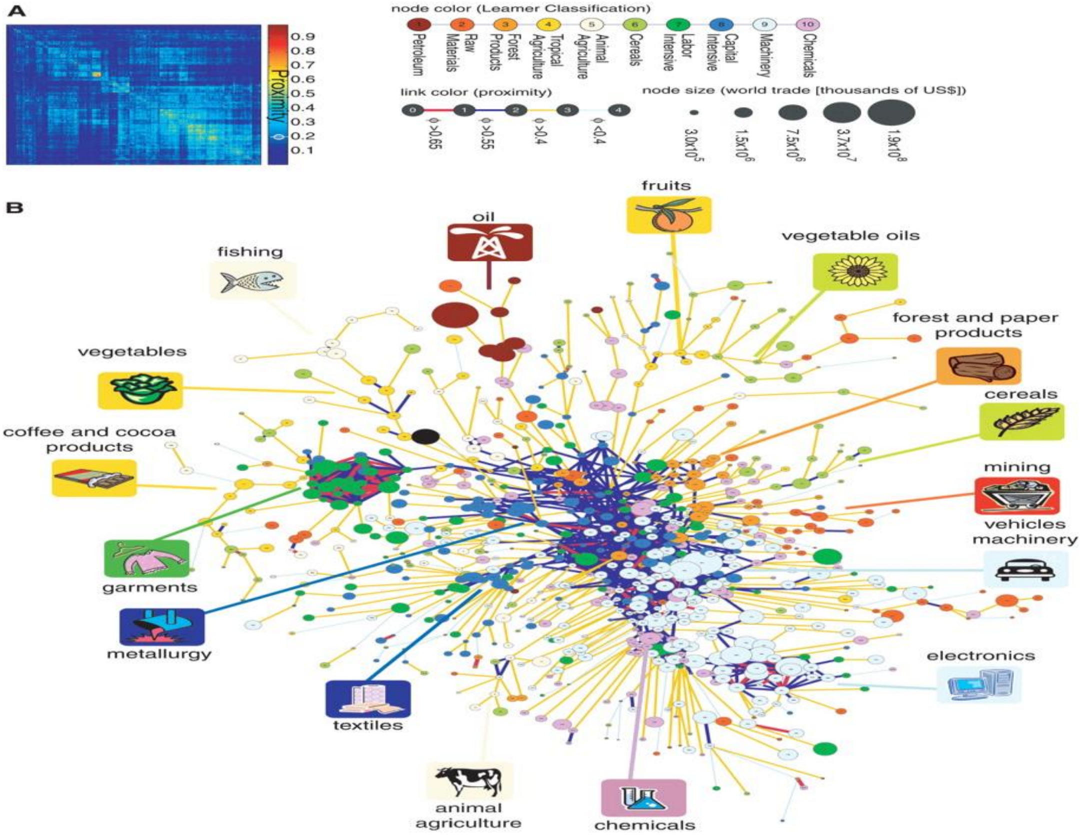
The other side of the scholars state that knowledge is indeed localized, but that it can reach further than only the region where the knowledge is produced. Territories do not rely only on their internal capacity to produce innovation, but also on their capacity to attract and assimilate innovation produced elsewhere. Knowledge does not stop spilling over just because of borders, such as city limit, state lines or national boundaries. Bottazzi and Peri (2003) found evidence of spillover effects between regions in the EU, with a positive impact of neighbouring regions' R&D efforts on local productivity within a 200-300km limit. Greunz (2003) found a positive and significant effect on local patenting activity of innovative efforts pursued in first and second order neighbouring regions (306km on average). The strength of this effect sharply decreases when reaching the third order neighbourhood (411km). This implies that knowledge can spillover to other regions but that the distance is not endless. Moreno, Paci and Usai (2005) also researched the pattern of innovation in one region and innovation in the other region. They found that innovative activity in a region is positively related to the level of innovative activity in neighbouring region located within 250km distance. Rodríquez-Pose and Crescenzi (2008) highlight the idea on existing tension between two forces: the increasingly homogeneous availability of standard 'codified' knowledge and the spatial boundedness of 'tacit' knowledge and contextual factors.

One factor that influences the level of spatial knowledge spillovers is the infrastructure (Maggioni, Nosvelli and Uberti, 2007). Advanced infrastructure influences the knowledge spillovers as places engage and learn from each other at a level that is much more intense than their relative spatial distance would suggest. Two places being closely situated to on another, but lack the support of an advanced transportation and communication infrastructure, result into lower levels of knowledge spillovers than the geographic proximity would suggest (Feldman and Kogler, 2010).

Technological proximity is another factor that affects the level of spatial knowledge spillovers (Moreno, Paci and Usai, 2005). Knowledge can only spill over if the involved party has an optimal cognitive distance, because only then it will be possible for the other party to absorb and implement the external knowledge that in turn results in technological change and enables innovation. For knowledge to spill over to other regions, there thus has to be a match between the industry of the specialised area and the sectors of the firms outside the territorial boundaries of a cluster, in order to create the highest spillover effect (Ascani et al., 2020). However, it does not have to be the exact same industry, but can also be a related sector. A theory linked to this is the related variety that states that regional growth happens when a wide range of sectors within a region are technologically related. The higher the number of technologically related industries in a region, the more learning opportunities are locally available, the more opportunities to make new recombinations and eventually the higher the regional growth (Frenken, van Oort and Verburg, 2007). The new activities are no random events or historical accidents as they are often strongly embedded in territorial capabilities and thus determined by path dependency. Kogler, Rigby and Tucker (2013) researched the domain of knowledge relatedness. The knowledge domains also can be based on co-occurrence of technology classes on patent documents. Kogler, Rigby and Tucker (2013) found that higher levels of average relatedness over time indicate that spillovers increasingly cluster within technology classes that are close to one another in technology space. In addition, higher levels of knowledge relatedness within cities are associated with faster rates of patenting per worker, which indicates that specialization spurs efficiency gains. Elsewhere, knowledge relatedness is related to patterns of technological diversification. Overall, it is the technological proximity of cities that is far more important to the flow of knowledge than geographical proximity. Franken, van Oort and Verburg (2007) state that bigger cities can afford specializing in an isolated sector, as due to the density, there are enough other economic sectors that can take the fall in case of an economic shock. On the contrast, smaller cities should diversify more in related sectors, in order to be resilient for when an economic shock occurs.

Relatedness is a variable that measures the related variety via the new activities that grow out of related activities, in which new activities combine and exploit capabilities from local related activities. Relatedness is measured via product space, which is the proximity between products based on co-occurrence of products in countries' export portfolios. In figure 3, the product space is visible for all kind of sectors. Figure 3B shows how related certain sectors are to one another, for instance, the fishing sector is an isolated sector as it is not related to much other sectors, but when it comes to chemicals there are more links to other sectors.

Figure 3: The product space
(A) Hierarchically clustered proximity
(B) Network representation of the product space



Source: Hidalgo et al., 2007.

Hidalgo et al. (2007) state that countries specializing in goods that are located in densely populated parts of “product space” can transition relatively easily among different product-sets. Countries specializing in products that are relatively isolated in product space have more narrowly defined sets of capabilities that hinder diversification. Rigby (2015) adds to this that when technologies are unrelated to the pre-existing technologies in a region, it had a higher probability to exit the region (Rigby, 2015).
So when it comes to the spatial knowledge spillovers, a certain technological proximity is needed for the other party to absorb and implement the external knowledge. Technological proximity is determined by the relatedness between the industry of the knowledge spillover and the receiver.

The last aspect that influence the level of spatial spillovers is the unintended geographical effect and an intentional relational effect of clusters. On the one hand, each cluster influences the neighbouring territories through a trickling down process of spatial diffusion (Magionni, Nosvelli and Uberti, 2007). On the other hand, technological and scientific knowledge developed in the cluster may be diffused and exchanged through a set of a-spatial networks (often structured in formal and contractual agreements between institutions) connecting each cluster with other clusters, whereas a spatial knowledge diffusion between clusters is created. In the exchange of knowledge between clusters, geographic proximity does not play a role, but the technological proximity is the one that sets the basis for an intentional relational effect.

2.6 Conceptual framework

It is clear from the literature that innovation is locally bounded and that science parks are beneficial places as there is a certain buzz that drives innovation even more. Municipalities try to form such science parks in order to boost innovation within the region. At places where innovation is, are also knowledge spillovers. While Magionni, Nosvelli and Uberti (2007) researched the impact of clusters on spatial knowledge spillovers, the relation between the existence of a science park on the level of innovation within and outside the municipality has not been researched yet. The existing literature offers the following hypothesises:

<u>Part 1: Innovation within municipalities with a science park</u>

Hypothesis 1:

Innovation in a municipality is positively related to the number of science parks in the same municipality

Hypothesis 2:

Innovation within a municipality is stronger positively related to the type of 'science park' and 'campus' than 'innovation district'

<u>Part 2: Innovation in neighbouring municipalities of science parks</u>

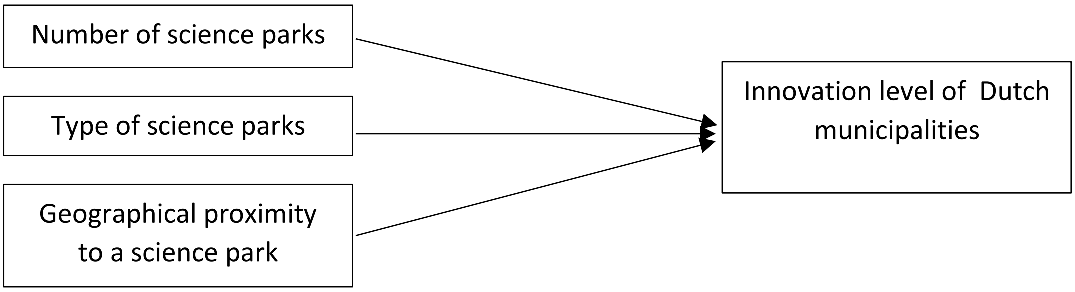
Hypothesis 3:

Innovation in a municipality is positively related to the number of science parks in neighbouring municipalities

Hypothesis 4:

Innovation within a municipality is stronger positively related to the type of 'science park' and 'campus' than 'innovation district' in neighbouring municipalities

Figure 4: Conceptual model



3. Methodology

With the selection of science parks as cases in the analysis, the purpose is to create an understanding of the influence of science parks on the innovation level within a municipality, and how the innovation spills over to neighbouring municipalities and if they can profit from the existence of a science park close by.
This research is a quantitative research that uses the research design of a multiple case study (Bryman, 2016). The cases, the municipalities with science parks and neighbouring municipalities in the Netherlands, are longitudinal cases as the municipalities are viewed over time. This research starts from 1980, while the opening of the first science park in the Netherlands is in the year 1931 in Arnhem. The reason for this is that data on innovation is available since 1978, but as it can take some years before patents are filed, 1980 is the first year taken into account in this research. From 1980 onwards, innovation within municipalities with science parks and neighbouring municipalities will be researched and thus makes it a multiple case study with longitudinal cases. To find out the answer on the research question, this research uses a multivariate analysis as is entails the simultaneous analysis of three or more variables (Bryman, 2016). To elaborate on the multivariate analysis, spatial econometrics is used to visualize the impacts of science parks on innovation. R will be used as a tool for the analysis, as it is easy to dive into the spatial econometrics.

3.1 Patenting data

In this research, innovation is tested using patent data. The use of patenting data to trace innovation is widespread and by now reasonable accepted (Castaldi, Frenken and Los, 2014). However, this has not always been the case as there is no consensus in the academic debate about how to measure innovation. There are multiple ways to research innovation such as R&D expenditures or labour force within the R&D sector (Fan, 2014). The downside to these indicators is that the focus relies on the input and not on the output of innovation. Moreover, R&D expenditures are not a unifying indicator as some regions can choose to invest in R&D while in other regions the investments come from companies. Another commonly used measurement, is to count the scientific papers from a geographically entity, while scientific papers do not always capture the newest innovations. The export value of high tech products is also a way of measuring innovation. However, the export value does not imply that the invention is also from that region and therefore this indicator is flawed too when measuring innovation (Fan, 2014). Overall, the patent count is the most suitable indicator of innovative activity at municipality level. Patents have great quantity and uniformity due to the role of the OECD that registers all the granted patents in the EU. The amount and quality of patents can easily be compared between, in this case, municipalities in the Netherlands (Castaldi, Frenken and Los, 2014). Thus, in this research the hypotheses are tested using patent data of the OECD (OECD Patent Quality Indicators database, 2021)(OECD REGPAT database, 2021)

3.2 Operationalisation

In this research all the municipalities in the Netherlands are included whether they do not have science park or patents. There was thus no use of sampling, because municipalities without patents or science parks also indicate important features for this research. Besides, it could be that this particular municipality is a neighbour of a municipality with a science park and therefore the information is valuable. In this case, the no sampling strategy makes the response representative and guarantees the external validity of the research. However, the Netherlands is still a case selection, which does imply that the outcomes cannot haphazardly be generalized to other countries.

The key independent variables in this research are locations of science parks in Dutch municipalities. This is measured via how much science parks are located in municipality *i* in year *t.* The source of the

data is a shapefile called Knowledge Location QGIS, which shows where the science parks are located and in which year they were established. The type ‘innovation hotspot’ is excluded in this research. It was unclear from the dataset what the definition and measurement was for naming something an innovation hotspot. Besides, some of the places were visited during fieldwork and the observation was that the innovation hotspot did not come close to the concept of a science park as discussed in this research. Therefore, it is chosen to exclude innovation hotspot from the dataset (see appendix A3). The variable science park, now consist of science (business) park, campus and innovation district all together, is used to indicate if there is a relation between the number of science parks and the patents in municipalities.
The second independent variable in this research is the type of science park. There are three different types: science (business) park, campus and innovation district. This variable captures the concept of organizational proximity whereas in organizational proximity, partners find the relevant organizational similarities that help them to work together, which is beneficial for interactive learning. At the science (business) park and the campus, there is a lot of collaboration between universities, academic centres, companies and R&D facilities (Ng et al., 2019). Therefore, it is expected that the organizational proximity present at these sights, influence the level of patents positively. This is different for the innovation district, because the aim is to support collaboration with other companies in order to generate economic growth. As the main goal at an innovation district is not to collaborate for innovation, it is expected that this type does not positively influence the level of patents within a municipality.

The first two control variables are population size and density and derived from the theory of agglomeration economies and social proximity. First, the agglomeration economies pinpoint the advantages to firms in the same industry when located together in the same region. Such a clustering can be determined by the availability of natural resources, closeness to specialized facilities or economic externalities such as being close to the market of supplies and buyers (Marshall, 2013). In this research the influence of the economic externality of being close to the market of suppliers and buyers, is being controlled by the variable density and population size. The higher the density and population size, the bigger the market for companies, which can raffle the relation between science parks and innovation within a municipality. Second, knowledge is best transmitted via face-to-face interaction, which happens, besides from geographical proximity, when there is social proximity. Social proximity is about embedded relations between agents at the micro-level (Werker, Ooms and Caniëls, 2016). For an organization to learn and innovate some social proximity is needed. Cities are key examples of such places of knowledge exchange, and in addition, they are places of creativity, dense locations of knowledge production and spillovers (Feldman and Kogler, 2010). In this research, the variables population size and density are controlling if the level of patents has not been raffled by the effect social proximity has on patenting. Besides, it also controls for the fact that in cities the level of patents is higher because the higher the density and population size, the higher the level of knowledge spillovers. Therefore, population size and density control the relationship between the numbers of science parks and the level of patents.
The third control variable is about the quality of the patent called quality index mean. The quality index mean is based on four components: number of forward citations (up to 5 years after publication); patent family size; number of claims; and the patent generality index (Squicciarini, Dernis and Criscuolo, 2013). This can be linked to the concept mentioned by Castaldi, Frenken and Los (2014), that states that the quality of the patent influences the innovation output of a region. While they focused on the influence of a breakthrough on the output of patents in a region, this research takes the quality index 4 as a way to measure the quality, because the breakthroughs had substantially more missing values in the dataset. As the quality index mean is high in a certain

municipality, this implies that there is a level of highly qualitied which might influence the relation between the number of science parks and level of patents, as the quality of the patents can also influence the level of patents. Important to keep in mind is that the more patents a municipality has, the more likely it has patents with a quality indicator, although having a quality indicator does not imply the value of a patent. Therefore the classes 1 (low), 2 (medium) and 3 (high), are made to see the actual score of the patents quality index per municipality (see appendix A1) Adding this variable tests if the level of patents is influenced by the quality of the patents which result influences the innovation output within a region.

The last variables needed, is made for the second part of the analysis and focuses on the effect of science parks on patents in neighbouring municipalities. Therefore, weighted variables are made to research the importance of the geographical proximity to a science park, and the impact of the different types of science parks. Geographical proximity refers to the spatial or physical distance between economic actors, both in absolute and relative meaning (Boschma, 2005). Short distances bring people together, favour information contracts and facilitate the exchange of tacit knowledge. The larger the distance, the less intensity of these positive externalities, and the more difficult it gets to transfer tacit knowledge. A weight matrix is made that tells which municipalities are neighbours of each other (see appendix C1). The distance matrix is based on a distance of 20km, which means that any municipality within 20km are considered neighbours. The choice for a 20km weight matrix is because almost every municipality in the Netherlands has a neighbour while at 15km that was not the case and with 30km, it could not really be considered as a neighbour anymore as e.g. Rotterdam and The Hague would then be neighbours of each other. Therefore, the weighted variable science park can tell us if municipalities within a distance of 20km of the municipality with a science park do profit from their geographical proximity to a science park.

Figure 5: Operationalisation of the variables used as the main concepts in this research

Concept	**Variable**	**Indicator**	**Data source**
		Dependent variables	
Geography of Innovation	Patents	Total number of OECD patents applied in year *t* assigned to inventors located in Dutch municipalities	OECD Patent Quality Indicators database, January 2021. & OECD REGPAT database, January 2021
		Independent variables	
Type of cluster	Science park	Total number of science parks per municipality *i* in year *t*	Knowledge location QGIS file of all the clusters within the Netherlands
Organizational proximity	Type of science park	Science (business) park Campus Innovation district	Knowledge location QGIS file of all the clusters within the Netherlands
		Controlling variables	
Agglomeration economies & Social proximity	Population size	Total inhabitants per municipality i in the year t	Statline CBS, Regionale kerncijfers in Nederlands, 2021.
	Density	Inhabitants per km² in municipality i in the year t	Statline CBS, Regionale kerncijfers in Nederlands, 2021.
Quality of innovation	Quality index mean	Mean quality indicator of patents based on: number of forward citations (up to 5 years	OECD Patent Quality Indicators database, January 2021.

		after publication), patent family size, number of claims, and the patent generality index 1= low, 2= medium 3= high (see appendix A1)	
		Weighted variable	
Geographical proximity	Weighted Science park	Municipalities within a distance of 20km to the municipality with a science park	Calculated from: Knowledge location QGIS file of all the clusters within the Netherlands & Statline CBS, Wijk- en buurtkaart 2020, 2021.
	Weighted type of science parks	Municipalities within a distance of 20km to the municipality with the types of science park: Science (business) park Campus Innovation district	Calculated from: Knowledge location QGIS file of all the clusters within the Netherlands & Statline CBS, Wijk- en buurtkaart 2020, 2021.

3.3. Formation of the dataset and used analyses

All the different sources of the variables are put together in one dataset. The exact steps in R are written in appendix A, which makes the research replicable and therefore reliable.

The first step is to merge two datasets of the OECD: OECD Patent Quality Indicators database and OECD REGPAT database. This results into a list of every patent in the world and with the given quality indicators. The next step is to subset the dataset in order to have only the patents of the Netherlands. The dataset is aggregated to have for each postal code the number of patents. As the patents are connected to a postal code, buurtshp2020 (CBS, 2021B) is needed to transfer the data to the name of the municipality. Buurtshp2020 (CBS, 2021B), is connected with the dataset of the OECD which result into a dataset of the level of patents per municipality and year.
From then, the other variables population size and density are added via CBS (2021A). Now the dataset consists of the municipality, year, number of patents, population size and density. The last step is to add the data of the science parks to it, whereas all the variables needed are included. As the dataset is based on the municipalities and years from 1980, it consist of panel data. In order to include a spatial component, the datasets needs to be connected to a shapefile. This is done for three separate years: 1980, 2000 and 2018 (CBS, 2021B).

3.3.1. Analysis: Innovation within municipalities with a science park- linear regression

In the first part of the analysis, R is used as a tool for the analysis, as it is easy to dive into the spatial econometrics. The maps for the three separate years are made via ESDA to see if there is correlation between science parks and the level of patents. Further, a linear regression with fixed effects is made (including 1980-2020) to see the relation between number of science and patents, and the influence of the control variables. In this research the outcomes are unreliable when there is a significance of $p>0.1$. This guarantees the internal validity and reliability of the research, because the significance points out, whether you measure what you want to measure (Bryman, 2016). As the maps are made and the regression is done, the first part of the analysis can answer the question if science park positively influence of patents within that same municipalities.
This analysis results into the following model:

$Patent_{m,t=}\beta*SP_{m,t} + \gamma*C_{m,t} + a_m+t_y+e_{m,t.}$

Where $\beta*SP_{m,t}$ is interpreted as the influence a science park has, in a certain municipality in a certain year, on the level of patents, in a certain municipality in a certain year. + $\gamma*C_{m,t}$ stands for the effect the control variables, population size, density and quality index, might have on the relation between science parks and patenting. a_m indicates the spatial factor taken into account in this analysis and t_y the time factor, which shows the use of panel data. The $e_{m,t}$ indicates the error controlled by the spatial fix regression.

3.3.2. Analysis: Innovation in neighbouring municipalities of science parks- spatial regression

In the second part of the analysis, R is also used as a tool for the analysis but a weighted variable is added to see if the patents in neighbouring municipalities are positively influenced by the presence of a science park. The weight matrix is based on the centroids of the municipalities and connects these centroids to other centroids if they are in a distance of 20km. This created a map (see appendix C1) which shows which municipalities are connected and thus are neighbours of each other. The analysis with the weight matrix is used with features of R in order to come to an answer to the research question. This part of the analysis is based on the year 2018. Firstly, because in 2018 all science parks are included as the newest ones were established in 2015. Besides, it can take some years before an effect of the presence of a science park can be seen because the filing of patents can cost several years. Secondly, it is the last year the data of the patents was complete. In 2019 and 2020, data was missing because not all patents were filed yet. Therefore, 2018 is the year with the most complete information and thus analysing this year is the most reliable.
The Local Moran's I test was the next step in answering the research question and calculated the overall spatial correlation between an observation at a science park and its neighbours. Creating lag variables was needed to see what happens with the spatial aspects when adding this variable in the regression of 2018 (OLS regression). A lag model and an error model gave more insights in the spatial relations, in this case if the science park can influence the level of patents in neighbouring municipalities.

$Patent_{m=}\beta*WSP_{m,t} + \gamma*C_{m,t} + a_m+ t_y+e_{m,t.}$

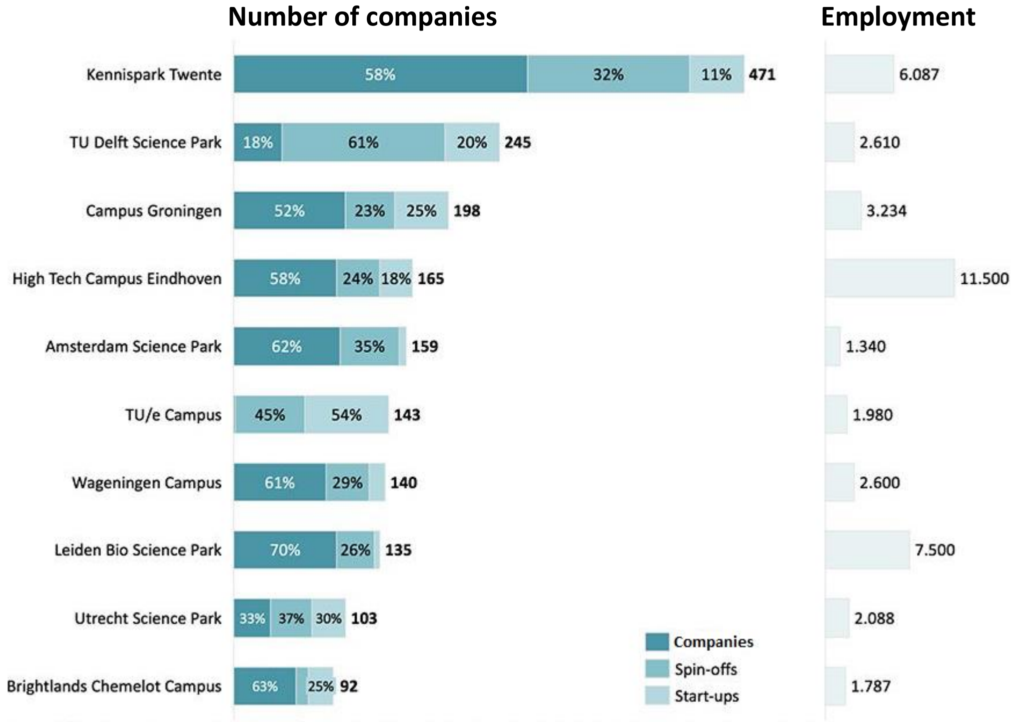
Where $\beta*WSP_{m,t}$ is interpreted as the influence a science park has located in a neighbouring municipality on the level of patents in a municipality. $\gamma*C_{m,t}$ stands for the effect the control variables, population size, density and quality index, might have on the relation between science parks and patenting within a municipality. a_m indicates the spatial factor taken into account in this analysis and t_y the time factor, which shows the use of panel data. The $e_{m,t.}$ indicates the error controlled by the spatial fix regression.

3.4 Case study: The Netherlands

When it comes to researching innovation, the Netherlands is an interesting case. First of all, while it is a small country, the output of innovation is high. In 2020, the World International Property Organization (WIPO) ranks the Netherlands at the fifth position when it comes to innovative countries in the wold, just behind Switzerland, Sweden, US and the UK (Rijksoverheid, 2020). On the European Innovation Scoreboard the Netherlands in named as an innovative leader from 2015 onwards and performs higher than the average of the EU-27 (Deuten, 2021). An explanation for these top positions, according to the Rijksoverheid (2020), is that innovation is in the Dutch DNA. Partly this has to do with the history where innovating is deeply rooted in culture, due to the fight of the constant flood risk the Netherlands had to deal with. In addition, the Dutch trade spirit demanded renewal in the shipbuilding and organizational structures. So therefore, it is not surprising that the Netherlands is still known for its innovative strength. The share of innovative companies in the Netherlands is with 50% on the EU-27 average in 2018 (Deuten, 2021). 27% of the companies is only focused on technological innovation, while the average in the EU is 14% (van Roekel, 2019). The Netherlands is strong in product innovation and co-operation with other inventors. On the contrary, the Netherlands scores low in the non-technological innovations, which include the field of marketing and organisational processes.

Second, besides innovation, the Netherlands is also well known for its campuses. The Netherlands is on the 2nd position of the world's top food exporting countries in 2020, thanks to the groundbreaking contribution of Wageningen University. Also, the Delfts innovative incubator is the second best in the world which focus relies in quantum computers, cars driven on solar energy and the Hyperloop. Not to forget TU/e which is well known for the start of Philips. In 2018, the Netherlands has an estimated number of 80 campuses spread throughout the country in all kind and forms: Science (business) park, campus, Innovation district and Innovation hotspot. Ten of them are in the adult phase when it comes to the ecosystem and business climate.

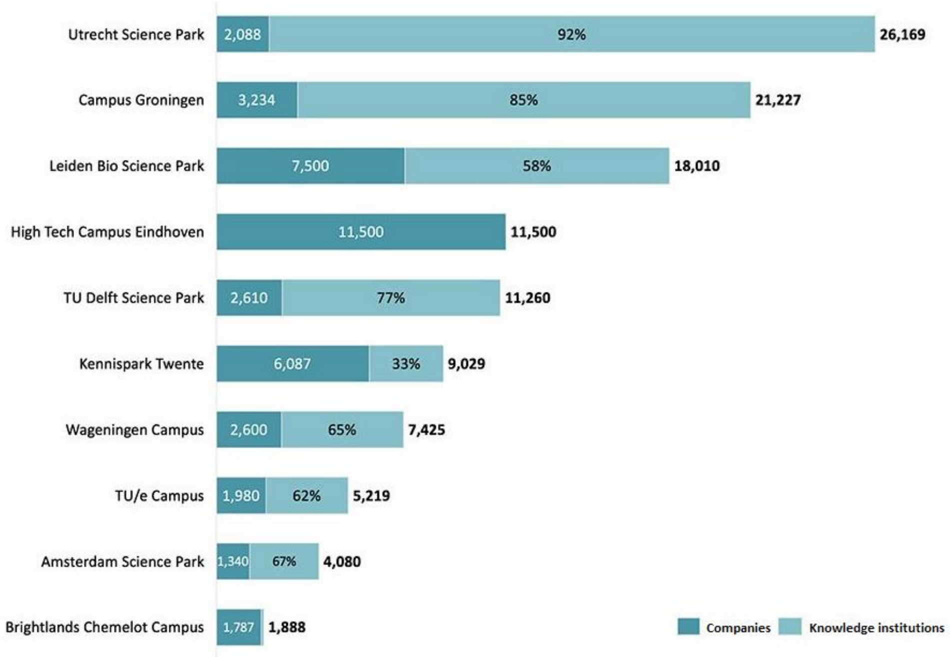
Figure 6: Top 10 most important campuses and science parks in the Netherlands, 2018



Source: BCI, 2018

In 2018, Kennispark Twente had the highest number of companies with a total of 471 companies. High Tech Campus Eindhoven is good for 165 companies but they offer far more employment, namely 11.500 jobs in total. This bring us to the third point why the Netherlands is an interesting case, because the campuses and science parks are drivers of employment. However, not only companies are located at campuses and science parks knowledge institutes offer employment opportunities.

Figure 7: Campuses and science parks with the highest employment in the Netherlands, 2018



Source: BCI, 2018

Figure 7, shows that Utrecht Science Park has the highest employment output, mostly caused by the jobs at the knowledge institutions. In addition, the knowledge institutions mostly cause the employment at Campus Groningen. Not only at the campuses are jobs being created, also in the municipality where the campuses and science parks are located in, job opportunities increase (Bruinenberg, 2018). The relative small country, the high innovation level, the large number of campuses which have international importance, and the employment output of these campuses make the Netherlands an interesting case to research the influence of science parks and campuses on innovation within municipalities and neighbouring municipalities.

4. Analysis: Innovation within municipalities with a science park

Before turning to the tests of the hypotheses, it is important to give an indication of the empirical importance of the differences being explained, and to give some ideas about the statistical properties of the explanatory variables and the controlling variables. Figure 8 gives some descriptive statistics, computed over 21157 observations.

Figure 8: Descriptive statistics (N=21157)

Variable	*Description*	*Min*	*Max*	*Mean*	*SD*
Total_patents	Total number of OECD patents applied in year *t* assigned to inventors located in Dutch municipalities	1	2715	15.21	102.79
Total_SP	Total number of science parks (including science business park, campus and innovation district) per municipality *i* in year *t*	0	3	0.03	0.23
Science_business_park	Total number of science park type 'science business park' per municipality *i* in the year *t*	0	2	0.02	0.16
Campus	Total number of science park type 'campus' per municipality *i* in the year *t*	0	2	0.01	0.14
Innovation_district	Total number of science park type 'innovation district' per municipality *i* in the year *t*	0	1	0	0.03
Population_size	Total inhabitants per municipality *i* in the year *t*	919	872757	35534.00	59206.15
Density	Inhabitants per km^2 in municipality *i* in the year *t*	21.0	6620.0	765.20	940.72
Quality_index_mean	Mean quality indicator of patents per municipality *i* in the year *t* with NA as no quality indictor, 1= low, 2= medium, 3= high	1	3	2.05	0.68

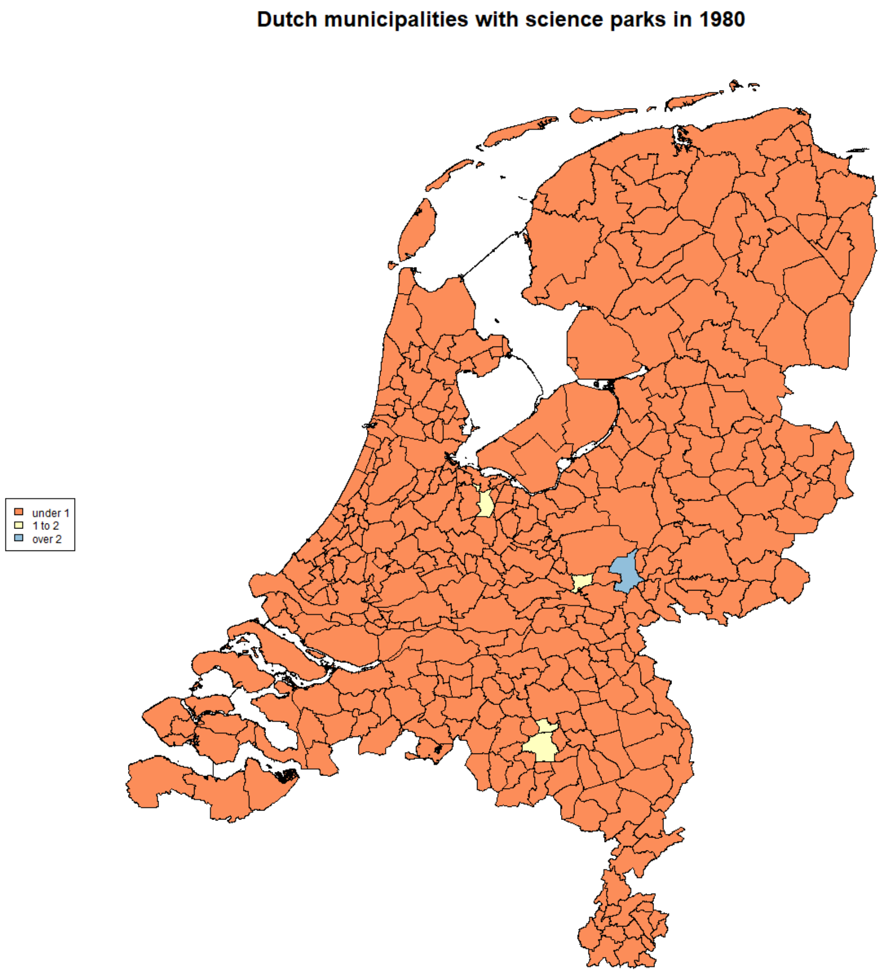
The output of the dependent variable, patents (*Total_patents)* varies strongly across municipalities and years. The highest number of patents is in Eindhoven in the year 2003 with a total number of 2715 patents. Over all the years, 1980 to 2020, the top 10 of total number of patents is dominated by Eindhoven. The first follow up is 's-Gravenhage (also known as The Hague) which had a total of 507 patents in 2008. The average number in Dutch municipalities is 15.21 patents per year.
The first independent variable is the total number of science parks per municipality (*Total_SP).* The highest number of science parks can be found in the municipalities Eindhoven, Amsterdam and Delft. Eindhoven in 2006 is the first municipality that had the three science parks. Delft has three science parks since 2013, and Amsterdam since 2015. The total number of science parks in the Netherlands in 2020 in this research is 45. As there are more 355 municipalities in the Netherlands, it is more likely that a municipality does not have a science parks, which results in an average number of 0.03 science parks in the Netherlands.
The second independent variable is about the different types of science parks. As figure 8 shows, there are three different types: Science (business) park, campus and the innovation district. In the Netherlands, there is a maximum of two science (business) parks (*science_business_park)* in a

municipality. These can be found in Delft, Arnhem and Hilversum. The maximum of total campuses (*campus)* in one municipality is also two and are located in Leeuwarden, Groningen, 's-Hertogenbosch, Rotterdam and Eindhoven. In the Netherlands, there are just two municipalities with an innovation district: Amsterdam and Eindhoven.
The first two controlling variables are population size and density. The municipality with the highest population size is Amsterdam in 2020 with 872757 inhabitants, followed by Rotterdam with 651157 inhabitants in 2020. The smallest municipality is Schiemonnikoog with the smallest number of inhabitants in 2016, namely 919. The mean population size in Dutch municipalities over all the years (1980-2020) is 35534.00. The highest density level is not in Amsterdam, but in 's-Gravenhage with 6620 inhabitants per km² in 2020. The second municipality with the highest density level is Voorburg, a municipality next to 's-Gravenhage, with 6382 inhabitants per km² in 1995. The smallest municipality when it comes to density is Schiermonnikoog, with a density level of 21. The mean density level in Dutch municipalities over all the years (1980-2020) is 765.20 inhabitants per km².
The last controlling variable is the quality index (*quality_index_mean)* which indicates the quality of each patent based on 4 components: number of forward citations (up to 5 years after publication); patent family size; number of claims; and the patent generality index. Only granted patents are covered by the index. In this research quality indicator 1 stands for low, 2 for medium and 3 for high. For every municipality in each year the mean quality indicator is calculated. There is a total of 645 observations in which the mean quality index is 3, 1928 observation where the mean quality index is 2, and 1125 observations with a mean quality indicator of 1. Therefore, this means that there are 645 observation of the 21157 that have a quality index of the category 'high'. The mean quality index in Dutch municipalities over all the years (1980-2020) is in the category medium as the number 2.05 indicates.

4.1 Mapping the patterns

The variables described in figure 8, are used for analysing the first hypothesis: Innovation in a municipality is positively related to the number of science parks in the same municipality.
To analyze this hypothesis it is important to first look at maps to see the diffusion of science parks and patents in the Netherlands, and if there is a correlation visible between the maps.
Figure 9 shows that there are five municipalities with science parks in 1980: Arnhem, Wageningen, Hilversum, Son en Breugel and Eindhoven. The blue municipality, Arnhem, consists of two science parks, while the other four municipalities only one science park is located. Looking at the map of the patenting levels in the Netherlands in figure 9, it shows that the patents are scattered throughout the country. Noticeable, is the enclave of municipalities with less than 3 and 3 to 7 patents in Gelderland, the municipalities at the cost with 61 to 106 patents (light blue) and with more than 106 patents (dark blue), and the dark blue colored municipality in the south of the Netherlands, Eindhoven. In comparison with the map of the science parks in 1980, a pattern can be seen. The municipality in the south that colors dark blue also consist of a science park. This same trend is visible for the red/yellow enclave in the east of the Netherlands where also two science park are located in. Even the municipality with two science park, Arnhem, colors light blue which means that there are 25 to 61 patents are filed. However, the two municipalities in the west that have a high level of patenting cannot be declared with the given information from the map of the science parks. While patenting levels and the location of science parks do differ substantially over the years, it is important to look at multiple patterns between science parks and patenting levels throughout the years. Therefore, figure 10 shows the municipalities with science parks and the patenting levels in 2000. New science parks are opened in 2000; in the east at the border of the Netherlands, there is now a municipality (Enschede) with one science parks, and also in the west there are two municipalities that now have one science park, Leiden and Delft.

Figure 9: Comparison between science parks and patenting levels in Dutch municipalities in 1980



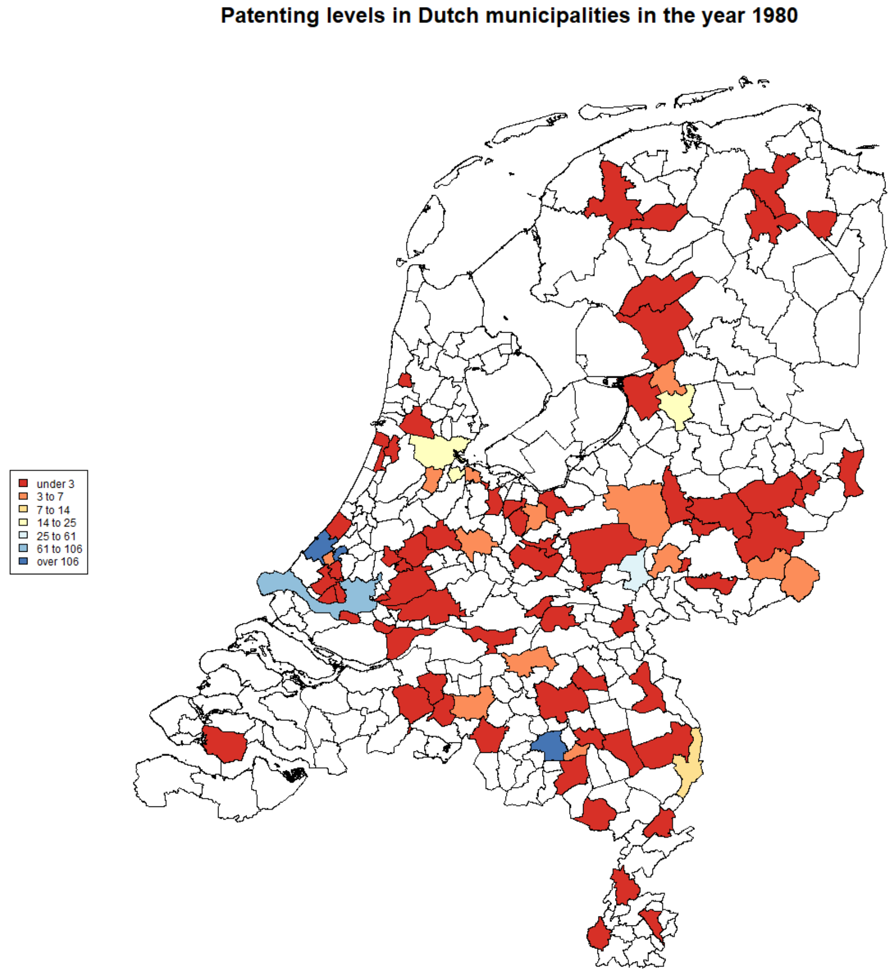
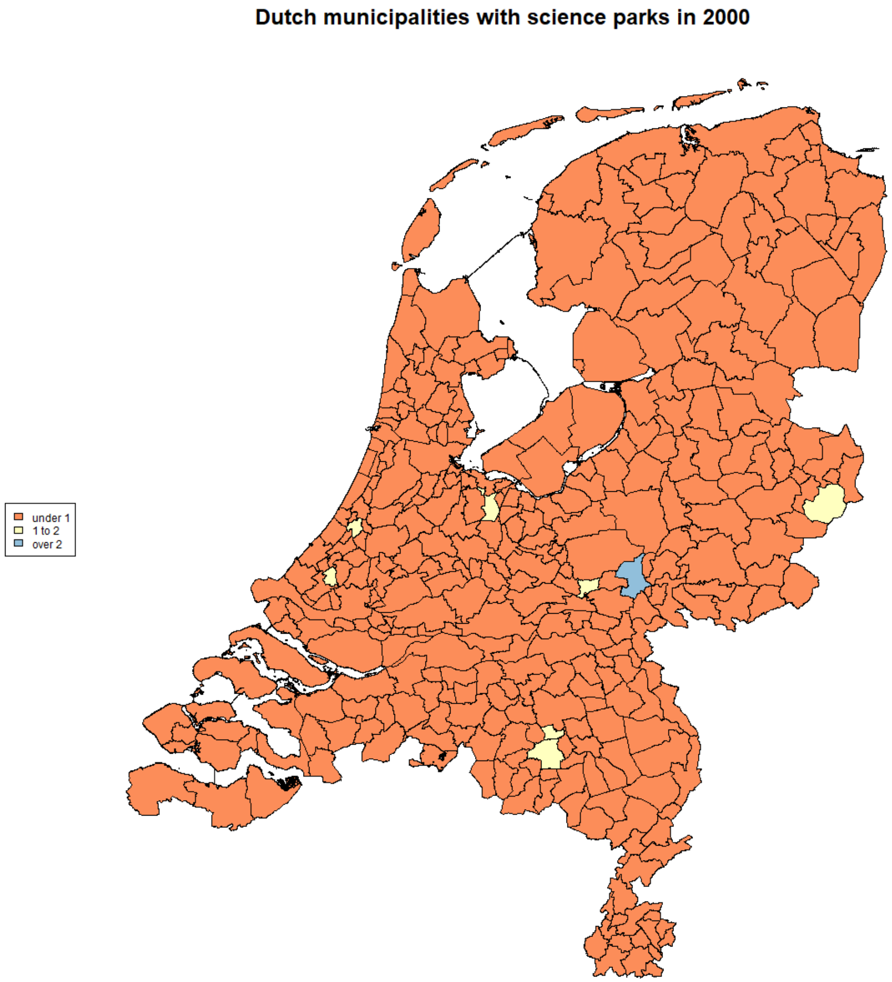
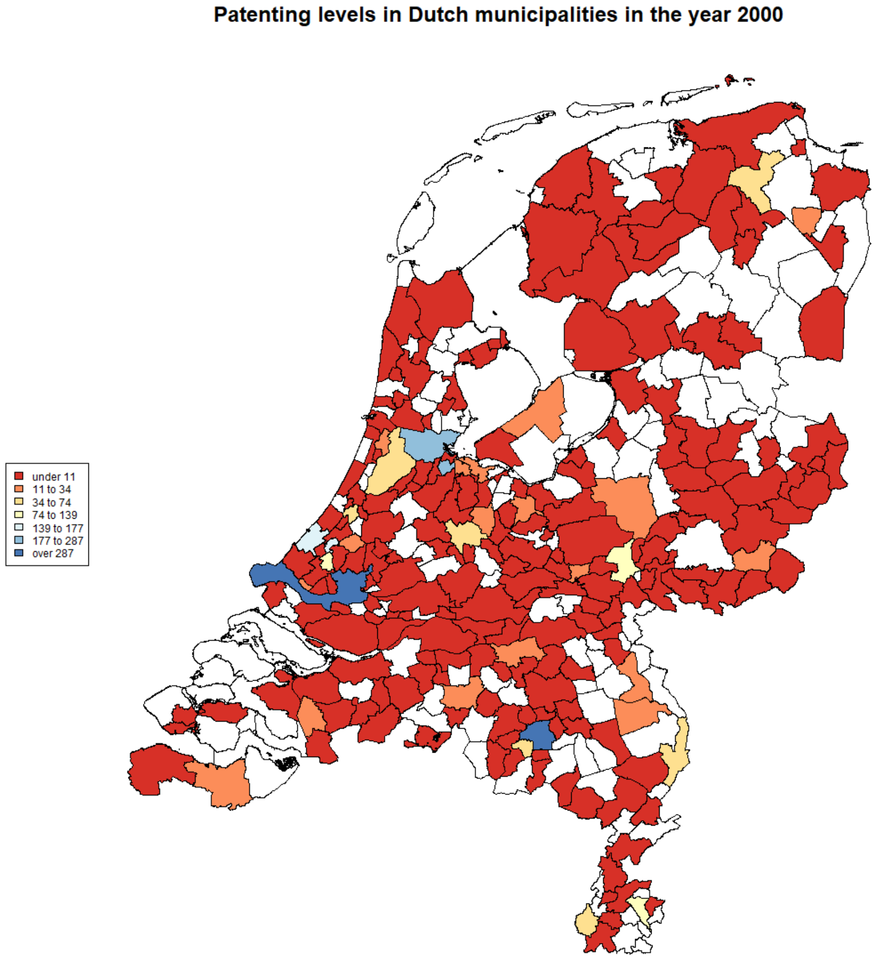


Figure 10: Comparison between science parks and patenting levels in Dutch municipalities in 2000

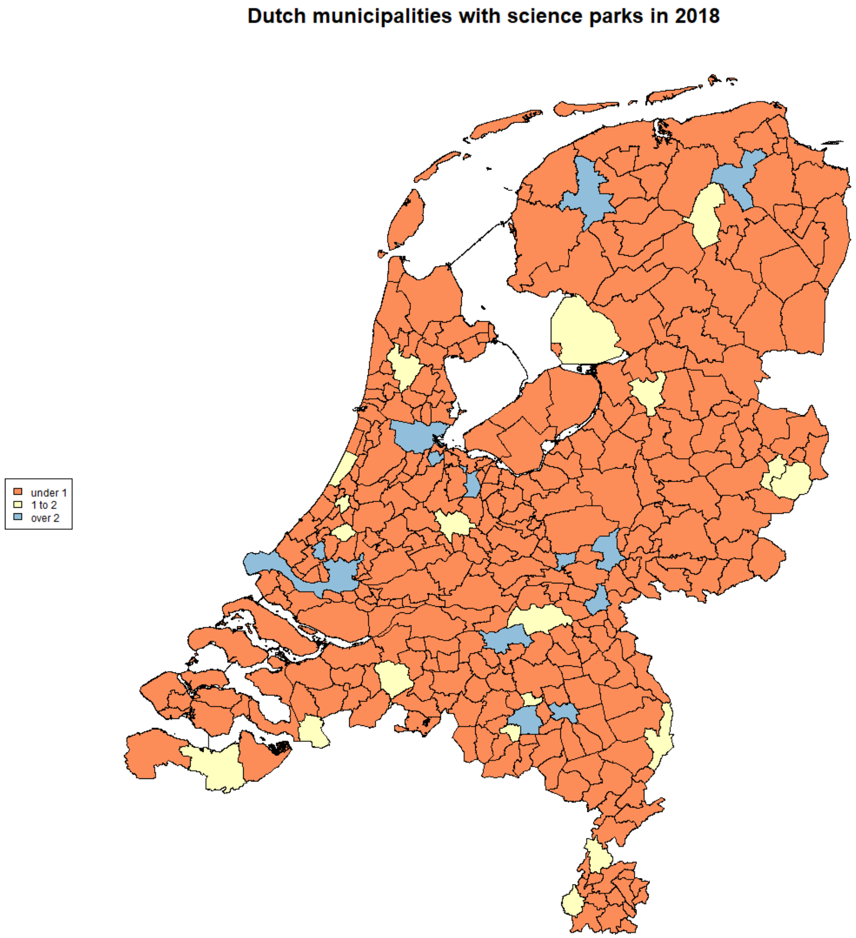


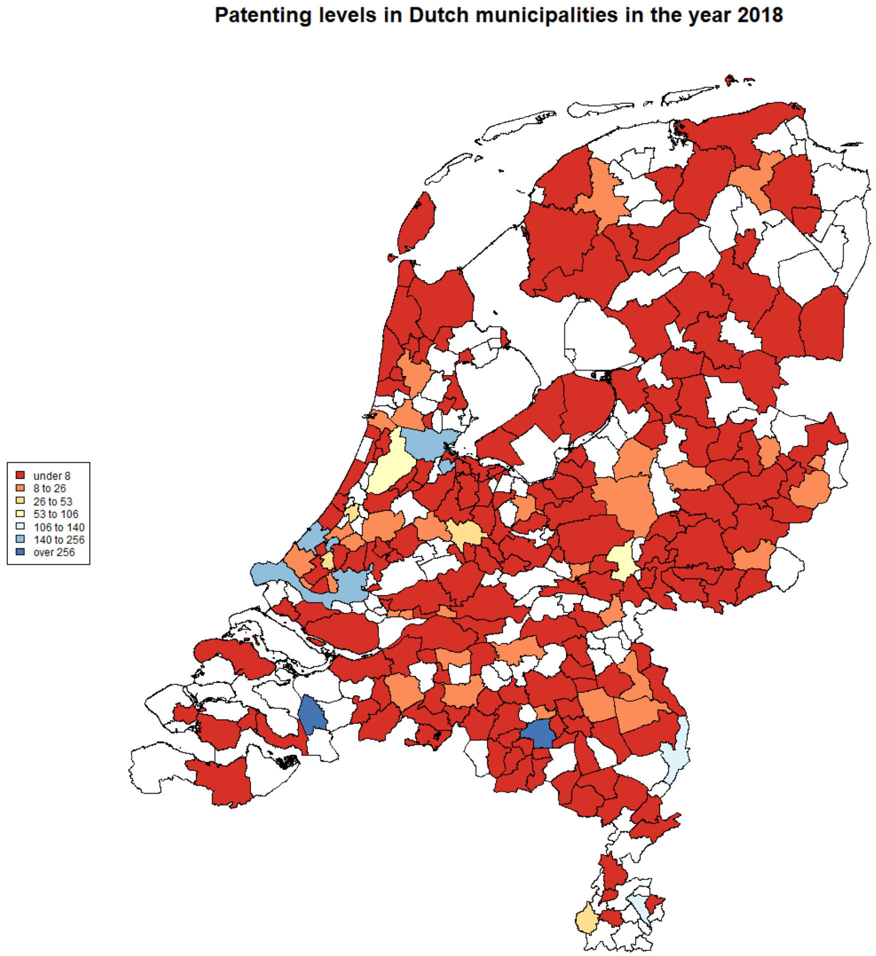


Furthermore, the map that illustrates the patenting levels in the Netherlands is more filled with patenting data then in 1980. This implies that in 2000 more municipalities applied for patents in comparison with 1980. However, the patenting maps cannot be compared over time as the levels of patenting differ substantially which would result into a skewed image. The maps can only be seen on itself and in comparison with the other thematic map; science parks in Dutch municipalities. There are two municipalities that colour dark blue (>287), in the south of the Netherlands, and in the west. In the south of the Netherlands, that same municipality also consist of a science park, the so-called TU/e campus in Eindhoven. Striking is also the red coloured neighbour municipalities (<11) and one yellow municipality (74-139) that are scattered around Eindhoven. The municipalities in the west that have a science park, also have more patents than their red neighbours (<11), that do not have a science park. The number of patents in Delft is good for a total of 73-139, and in Leiden for 34-74. Enschede, the municipality at the border of the Netherlands with one science park, has a total number of under 11 patents. The municipality that colours blue in the map of the science parks, Arnhem, is good for an output of 74 to 139 patents in 2000. The other municipalities with a higher level of patenting cannot be declared with the given information from the map of the science parks. The last year that is taken into account for comparing the map of the science parks in Dutch municipalities to the patenting levels, is 2018. The reason for this is that all the science parks until now are established. The newest science parks, opened in 2015, are ‘s-Hertogenbosch, Amsterdam, Noordenveld and Veldhoven. Besides, it is also the year that the information about the patents is the most accurate as it can take some years before a patent is acknowledged by the patenting center, while patents in 2019 and 2020 are not filed yet. So, when it comes to the data of the science parks and the patents, the year 2018 has the most complete information. Looking at the map (figure 11) with the science parks, it is visible that there are more science parks in the Netherlands than in 2000. Thereby, there are also more municipalities that have more than one science park. In the north of the Netherlands, municipalities Leeuwarden and Groningen both consist of 2 or more science parks. In the west and the center of the Netherlands the municipalities Rotterdam, Amsterdam and Hilversum light up blue and thus have 2 or more science parks. Wageningen, Nijmegen and Arnhem, located in the east of the Netherlands, all have 2 or more science parks located in their municipalities. In the south of the Netherlands ‘s-Hertogenbosch, Helmond and Eindhoven all allocate two or more science parks. Furthermore, the yellow colored municipalities are all spread throughout the country, which result that every part of the Netherlands at least has one municipality with a science park. When looking through your eyelashes at the map of the patenting levels in Dutch municipalities in 2018, the map colors mostly red and orange. This means that in the most municipalities the patenting levels are under a total of 8 or between 8 and 25. However, some exceptions can be made, as there are two municipalities that have over 256 patents and thus color dark blue: Eindhoven in the south of the Netherlands, and Bergen op Zoom in the southeast of the Netherlands. Interesting is that Eindhoven has 2 or more science parks, but that Bergen op Zoom does not have any science park. The municipalities Amsterdam, Rotterdam and The Hague have a total output of 140 to 256 patents. Amsterdam and Rotterdam both allocate two or more science parks, while The Hague does not have any science park. When looking at the yellow municipalities (26-53 and 53 to 106) there seems to be a correlation with the municipalities that also have a science park. However, in the north of the Netherlands the municipalities Leeuwarden and Groningen both also consist of two or more science parks, but their patenting levels are not substantially higher than in Dutch municipalities that do not have a science park. Even the municipality Woensdrecht that has one science park, stays white in the map of the patenting levels, which means that in 2018 there were no patents filed in this municipality.

In sum, the maps of 1980 and 2000 would assume that there is a correlation between the location of

Figure 11: Comparison between science parks and patenting levels in Dutch municipalities in 2015





a science park and the level of patenting. Municipalities with a science park also indicate a higher level of patenting. In 2018, this correlation is less visible as more and more municipalities have filed patents. In some municipalities as e.g. Eindhoven, Rotterdam and Amsterdam the pattern is seen that they have a science park and an exceptionally high output of filed patents. While in other municipalities, as Leeuwarden and Groningen, that also own two science park or more, their patenting level does not differ substantially compared with municipalities that do not have a science park. A downside of these maps is that they capture one moment in time, while patenting levels fluctuate. Thereby, filing for a patent can take several years, which means that if a science park is opened in a certain municipality, it can take years before an effect of this science park can be seen. So in order to see if there is correlation between the science parks and the patenting levels in municipalities, a regression needs to be made to see the impact of science parks over all the years and not the grasp of time the maps give us.

4.2 Fixed effects regression

The regression in figure 12 can give us an answer on hypothesis one and two: Innovation in a municipality is positively related to the number of science parks in the same municipality and innovation within a municipality is stronger positively related to the type of 'science park' and 'campus' than 'innovation district'.

Figure 12: Fixed effects regression, model independent variable total_patents

Independent variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Total_SP	43.972*** (2.894)			
Science_business_park		8.659* (5.039)	4.762 (6.180)	0.039 (0.618)
Campus		29.476*** (4.292)	18.302*** (5.129)	0.070 (0.661)
Innovation_district		291.356*** (14.301)	121.684*** (16.732)	
Population_size			0.0003** (0.0001)	0.00002 (0.00002)
Density			-0.003 (0.006)	-0.001*** (0.0005)
Quality_index_mean				0.063 (0.101)
Observations	8163	8163	5113	2145
R^2	0,740	0.751	0.849	0.922
Adjusted R^2	0,727	0.738	0.837	0.906

*p<0.1; **p<0.05; ***p<0.01

The first model tests the relation between the total number of science parks and level of patents in Dutch municipalities. The result shows that the relationship is significant with a p-value of <0.01. The direction of the relation is positive, because if the number of science parks goes up by 1, the total amount of patents also goes up with 43 patents. The R^2 of 0.740 indicates that the model explains 74% of the variation in the data.

In model 2 the explanatory variables Science (business) park, campus and innovation district are added. The variable *Total_SP* is excluded as the three different types of science parks, together form the *Total_SP*. There is also a relation between the explanatory variables. The relation between the existence of the type science (business) park is significant, with one more science (business) park the

number of patents goes down with 8. This trend is the same for the variable campus that has a higher significance than the science (business) park, but with one more campus, the total amount of patents goes up with 29. The impact of a campus on the levels of patenting is thus higher than the impact of a science (business) park. Striking, is the impact the innovation district has on the level of patents, as with a significance of $p<0.01$, and a rise of patents in 291, the innovation district has the highest effect on the total output of patents. Therefore, for a municipality to have the highest patenting output, an innovation district is the most beneficial. This is different than theories suggested. The types of science parks are connected to the theory of social proximity, whereas partners find the relevant organizational similarities that help them to work together, which is beneficial for interactive learning. At the science (business) park and the campus there is a lot of collaboration between universities, academic centres, companies and R&D facilities, while at an innovation district the focus is on collaboration with other companies via research facilities and pilot plans which businesses can use in order to generate economic growth. So the intensive collaboration between multiple agents at a science park and campus suggested that these places would have a higher output of innovations, but the outcomes show. Besides, model 2 is a slightly better predictor for the data variation actual data than model 1 because the R^2 increased to 0.751.
In model 3 the control variables population size and density are added. These variables can show if agglomeration economies and social proximity are intertwined in the relationship between the type of science parks and the effect on patents. Population size is significant while the strength of the relation is low as population size increases the total patents increase with 0.0003. Density is not significant, which implies that density does not play a role in the level of patenting. Adding these variables does not change the significance of campus and the innovation district, which means that these two types still positively influence the level of patents within that same municipality. Again, the impact of the innovation district on patents is higher than the impact of a campus. The relation between the presence of a science (business) park and the total patents within a municipality is not significant anymore which insinuates that the concept population size influences the relation between science (business) parks. This result implies that agglomeration economies and social proximity do affect the relation between science (business) park and patenting. The exact reason for this exogeneity needs to be researched more, but a possible explanation could be that science (business) parks rather tend to locate at places close to cities because e.g., it is a more attractive place for businesses due to closeness to the market or that universities are more situated in cities. So, in particular, population size influences the relation between science (business) park and patenting, but not for a campus and an innovation district. In comparison with model 2 the R^2 increased to 0.849.
Looking at model 4, the new variable quality index mean is added, and does affect the relation between the type of science parks and the total level of patents. The relations between the campus and patenting is also not significant anymore. The disappearing of the innovation district is related to the fact that there are only two municipalities with an innovation district, which apparently do not have patents with a quality indicator. However, the quality index on itself is not significant which shows a skewed image on the effect of the level of patents. Model 4 has a R^2 of 0.922, which implies that the model explains 92.2% of the data variation.

In sum, figure 12 shows that the relation between the number of science parks and the level of patents is significant and that if the number of science parks goes up by 1, the level of patents goes up by 43. This suggest that innovation in a municipality is positively related to the number of science parks in the same municipality, and thus hypothesis 1 is confirmed.
When it comes to the relation between the type of science park science (business) park, campus and innovation district, the variables are significant and when the number of each type goes up by 1, the

level of patents increases. This implies that innovation within a municipality is positively related to the type of science (business) park, campus, and innovation district. However the impact of an innovation district is higher positively related than science (business) park and campus, which means that hypothesis 2 is rejected.
The controlling variable population size is significant and influences the relation between a science (business) park and patenting which causes exogeneity. Density and quality index mean are not significant, so from this analysis it cannot be interpret if these two variables influence the relation between science parks and patenting.

5. Analysis: Innovation in neighbouring municipalities of science parks

This analysis focuses on the impact of science parks and the type of science park on patents in neighbouring municipalities of the science parks. Therefore, it tries to find out the role of geographical proximity to a science park on the level of innovation. Therefore, it answers hypotheses 3 and 4; innovation in a municipality is positively related to the number of science parks in neighbouring municipalities, and innovation within a municipality is stronger positively related to the type of 'science park' and 'campus' than 'innovation district' in neighbouring municipalities. However, this analysis focuses only on the year 2018 while analysis 1 captured the years 1980-2020. The reason for this is that the effect only could be measured for one year and not all the years together. Firstly, the choice for 2018 is because all science parks are included as the newest ones were established in 2015. Besides, it can take some years before an effect of the presence of a science park can be seen because the filing of patents can cost several years. Secondly, it is the last year the data of the patents was complete. In 2019 and 2020, data was missing because not all patents were filed yet. Therefore, 2018 is the year with the most complete information and thus analysing this year is the most reliable.

Looking at figure 11 in some cases the neighbouring municipalities of science parks have higher patenting levels. This is visible for Eindhoven in the south where many neighbouring municipalities are coloured red and have a patenting level under 8 in 2018. The same is the case for the science parks located in the west of the Netherlands, which are also surrounded by municipalities that have filed patents. This pattern is also visible for Amsterdam and in the east of the Netherlands where the science parks in municipalities Wageningen, Arnhem, Nijmegen, Enschede and Hengelo. It seems like there is a pattern when taking a municipality with a science park as central point, and looking at the patenting levels in the municipalities surrounding it. However, this is not the case for all the municipalities that are close to a municipality with a science park. For instance, in the north of the Netherlands the science parks in Groningen and Leeuwarden are not surrounded by municipalities that all have filed patents in 2018 as some municipalities stay blank. This is the same for the science parks located in Limburg, in the south of the Netherlands that do not show the pattern of that neighbours have filed patents. So looking at the maps, it is not clear what the exact pattern is, and therefore a regression needs to be made.

5.1 Spatial regression

There is a need for spatial regression models to see if the patents in a municipality are correlated with the science parks in the neighbouring municipalities. The Local Moran I test can give a first indication about the role of spatial dependency and describes the correlation between an observation and its neighbours. The test statistic is -1.0677 with a p-value of 0.8572 that indicates that the correlation is pure random and that there is no correlation between the number of patents and the number of science parks in a neighbouring municipality as the p-value is >0.1.

To unfold, there are more ways to look into the correlation between patenting level and a science park in a neighbouring municipality and the explanatory variables. Before making a regression that shows the effect of innovation in neighbouring municipalities of science parks and the type of science parks, a normal regression of the year 2018 needs to be made to see the exact relation when adding a weighted variable.

Figure 13: Regression model dependent variable total_patents 2018

Independent variables	*Model 1:*	*Model 2:*	*Model 3:*	*Model 4:*	*Model 5: OLS*	*Model 6: OLS*
Total_SP	90.037*** (13.977)				90.968*** (14.078)	
wSP					24.171 (31.614)	
Science_business_park		-36.930** (17.446)	-15.904 (16.929)	11.332*** (2.400)		-14.714 (17.304)
wSBP						15.613 (38.325)
Campus		63.776*** (17.035)	117.891*** (18.175)	-1.689 (2.004)		118.616*** (18.352)
wCAMP						-0.095 (39.394)
Innovation_district		917.711*** (64.866)	1,108.201*** (67.873)			1,108.563*** (68.480)
wINND						-73.205 (120.251)
Population_size			-0.001*** (0.0001)	0.0001*** (0.00002)		-0.001*** (0.0001)
Density			0.008 (0.006)	0.001 (0.001)		0.008 (0.006)
Quality_index_mean				0.282 (1.473)		
Constant	1.211 (8.282)	7.591 (5.977)	26.277*** (7.585)	0.764 (3.289)	-3.339 (10.237)	0.764 (3.289)
Observations	225	225	216	46	224	215
R^2	0.157	0.567	0.652	0.678	0,159	0,653
Adjusted R^2	0.153	0.561	0.644	0.638	0,151	0,640

*p<0.1; **p<0.05; ***p<0.01

Model 1, 2, 3 and 4 are normal regressions while model 5 and 6 are spatial regressions. In comparison with figure 12, there is logically not much difference for only the year 2018. Model 1 still is significant with a positive relation. In model 2 some changes are visible when comparing it with model 2 in figure 12. The type's campus and innovation district are both still significant and have a positive relation. Science (business) park, on the contrast, has now a significance of p<0.05 and a surprisingly negative impact on patenting. However, when looking at model 3, the same relations for science (business) park, campus and innovation district arise as in figure 12. Adding the variable quality index mean in model 4, causes a drop in observations. Probably, the root for this cause relies in the measurement of the quality index mean. A part of the quality index mean is measured via citations and as the years pass by, the number of citations also can increase. This means that 2018 is too close and that *quality_index_mean* cannot be measured to its fullest. Another factor that can play a role is that there are less patents because it is only one year, so proportionally also less patents signed with a quality index. The drop in observations in model 4 causes an insignificance in campus, while science parks are now significant. So, model 4 shows a skewed image and therefore the spatial regression in model 6 is based on model 3. In model 5, the spatial lag variable *wSP* is added and has a value of -24.171, but is not significant. In model 6 the variables *wSBP, wCAMP* and *wINDD* are added. These weighted variables are not significant, hence do not change the relation between and the type of science park in a neighbouring municipality. However, there are more ways to test a spatial regression; the error model and the lag model. The error model takes up the error terms of the neighbours as an extra variable. It could be that there are unknown municipality factors determining the relationship between science parks and the patents that are not included in the explanatory nor the control variables. The lag model takes into account the interaction in municipality x and municipality y, e.g. innovation in municipality x drives up innovation in municipality y or the other way around.

Figure 14: Three spatial regression models about dependent variable total_patents in 2018

Independent variables	*Model 1: OLS*	*Model 2: ErrorMod*	*Model 3: LagMod*	*Model 4: OLS*	*Model 5: ErrorMod*	*Model 6: LagMod*
Total_SP	90.968*** (14.078)	91.5623*** (13.9371)	92.0971*** (13.9428)			
wSP	24.171 (31.614)	29.6766 (30.4941)	39.0557 (32.9399)			
Science_business_park				-14.714 (17.304)	-1.5267e+01 (1.6759e+01)	-1.4233e+01 (1.6966e+01)
wSBP				15.613 (38.325)	1.4021e+01 (3.6231e+01)	1.1127e+01 (3.8557e+01)
Campus				118.616*** (18.352)	1.1931e+02*** (1.7872e+01)	1.1914e+02*** (1.7948e+01)
wCAMP				-0.095 (39.394)	1.3735e+01 (3.7012e+01)	1.1205e+01 (3.9710e+01)
Innovation_district				1,108.563*** (68.480)	1.1116e+03*** (6.6685e+01)	1.1091e+03*** 6.6922e+01
wINND				-73.205 (120.251)	-1.0467e+02 (1.1389e+02)	-1.9590e+01 (1.0883e+02)
Population_size				-0.001*** (0.0001)	-6.3245e-04*** (9.3919e-05)	-6.2368e-04*** (9.4354e-05)
Density				0.008 (0.006)	9.2308e-03* (5.4395e-03)	8.3620e-03 (5.5646e-03)
Constant	-3.339 (10.237)	-4.1973 (9.5020)	-3.9695 (10.1360)	0.764 (3.289)	2.5820e+01*** (7.9155e+00)	2.6452e+01*** (8.4796e+00)
Observations	224	224	224	215	215	215
Rho/Lambda		-0.082	-0.085		-0.098	-0.059
R^2	0,151	0.162	0.163	0,640	0.080	0.654

*p<0.1; **p<0.05; ***p<0.01

In Model 2, the Error model shows that *wSP* has a positive correlation with the level of patents as the science park in a municipality goes up by 1, the level of patents in neighbouring municipalities goes up with 29. However this correlation is not significant and thus there is no spatial effect. The Lambda shows a negative correlation, but the correlation is so close to 0 (0.082) that it is almost negligible.
In the Lag model, (model 3) *wSP* has a positive correlation, which means that if the number of science parks goes up by 1, the number of patents in neighbouring municipalities also goes up by 39 patents. Again, the *wSP* is not significant and therefore there is no spatial correlation between science parks and level of patents in neighbouring municipalities. The Rho in the Lag model shows a slightly negative correlation, but -0.085 is so close to 0 that the correlation is negligible.
As the statistic parameter p-value of ErrorMod is 0.3371 and of LagMod 0.3397, the ErrorMod is the best predictor (see appendix C3). However, the p-value is >0.1 and thus still insignificant.

When looking at the spatial effect of the type of science parks on patenting in the error model (model 5), *wSBP* and *wCAMP* have a slightly positive impact on the level of patenting, while *wINDD* impact is slightly negative. Though, the three weighted variables are not significant which means that there is no spatial effect. The lambda in model 5 is -0.098, which indicates a slightly negative correlation. In the Lag model, model 6, *wSBP and wCAMP* have a slightly positive impact, and *wINDD* a slightly negative impact, but the explanatory variables are again not significant. The Rho of -0.059 shows a slightly negative correlation but is negligible as the number is so close to 0. The static parameter p-value of ErrorMod (model 5) is 0.20547, whereas the ErrorMod is the best predictor (see appendix C3) because the p-value of LagMod 0.48695 (model 6). However, the p-value is >0.1 and thus still insignificant.

To conclude, the Moran I, figure 13, and figure 14 all show that that the weighted variable of the science parks is not significant, neither the weighted variables of the type of science parks. This means that there is no spatial effect between the number of science parks and the level of patents in neighbouring municipalities and between the type of science parks and the patenting output in neighbouring municipalities. While in both cases the ErrorMod gives the best impression of the correlation, the model is still insignificant. Hence, hypothesis 3 and 4 are rejected, thus innovation in a municipality is not positively related to the number of science parks in neighbouring municipalities nor to which type of science park whatsoever.

6. Conclusion

This research focused on the impact of science parks in the Netherlands on the innovation within municipalities and in neighbouring municipalities. The Netherlands is an interesting case as it is a small country with a high level of innovation and ranks high in the list of innovative countries. Besides, the Netherlands is well known for its campuses including Wageningen University, Delft and TU/e. At a science park, there is a certain buzz where knowledge is in the air and businesses, universities, higher education institutes and research organisations seek to facilitate collaboration with innovation as a main goal. The features of this site makes a science park attractive places where it creeps of talented people. There is a high activity of innovation at science parks and municipalities try to form such parks in order to stimulate innovation in the region. While innovation is sticky, knowledge can travel through space with some aspects making the transfer of knowledge easier for instance, via face-to-face contacts or having the same type of technology. These knowledge spillovers can contribute to the process that the region benefits from the existence of a science park in terms of innovation. Aspects researched are the number of science parks in a municipality, the type of science park and if geographic proximity to a science park plays a role in the innovation output.

To summarise, the analysis started with mapping the patterns between a science park and the patents within a municipality for the years 1980, 2000 and 2018. In 1980, there were just five municipalities that consist of a one or more science parks. Looking at the maps of the patenting levels within that same year, it seems like there is a pattern between municipalities with a science park and a higher output of patents. This same correlation is visible for the year 2000. More science parks are opened and the patenting levels in the same municipalities do show higher levels of patenting. In 2018, this correlation is less visible as more and more municipalities have filed patents, and more science parks are opened. In some cases, e.g. Eindhoven, Rotterdam and Amsterdam the pattern is seen that they have a science park and an exceptionally high output of filed patents. While in other municipalities, as Leeuwarden and Groningen, that also own two science park or more, their patenting levels do not differ substantially compared with municipalities that do not have a science park.

The analysis continued with a fixed effect regression showing that the relation between the number of science parks and the level of patents is significant and that if the number of science parks goes up by 1, the level of patents goes up by 43. This suggests that innovation in a municipality is positively related to the number of science parks in the same municipality. When it comes to the relation between the type of science park science (business) park, campus and innovation district, the variables are significant and when the number of each type goes up by 1, the level of patents increases. Innovation within a municipality is thus positively related to the type of science (business) park, campus, and innovation district, but it is the innovation district that has the highest influence on the level of patents. This is different from the theory that suggest that science (business) parks and campuses do have a higher impact on innovation due to the extensive collaboration between multiple agents, such as businesses and knowledge institutions. The relations are controlled for the variables population size, density and quality index mean. Density and quality index mean are not significant, so from this analysis it cannot be interpret if these two variables influence the relation between science parks and patenting. On the contrast, population size is significant and influences the relation between a science (business) park and patenting levels, which causes exogeneity.

The last part of the analysis focused on the impact of science parks on neighbouring municipalities in 2018. Looking at the map, in some cases the neighbouring municipalities of science parks have higher patenting levels. It seems like there is a pattern when taking a municipality with a science park as central point, and looking at the patenting levels in the municipalities surrounding it. However, this is not the case for all the municipalities that are close to a municipality with a science park. The maps do not show the correlation between a science park and patenting levels in neighbouring municipalities. The Moran I, on the other hand, shows if there is a spatial correlation between science parks and patenting in neighbouring municipalities. The test statistic of -1.0677 with a p-value of 0.8572 indicates that the correlation is pure random and that there is no correlation between the number of science parks and the number of patents in a neighbouring municipality as the p-value is >0.1. The correlation is further explored by a spatial regression, which includes the weighted variables of the science parks and the type of science parks. The OLS, ErrorMod and LagMod all show that that the weighted variable of the science parks is not significant, neither the weighted variables of the type of science parks. This means that there is no spatial effect between the number of science parks and the level of patents in neighbouring municipalities and between the type of science parks and the patenting output in neighbouring municipalities. This implies that innovation is sticky, and hard to spillover to the region. Science parks do not contribute to the knowledge spillovers outside their municipality, and therefore neighbouring municipalities do not profit from a science park in terms of innovation.

To conclude, the analysis shows that the level of patents within a municipality is positively related to the number of science parks in the same municipality. Innovation within a municipality is positively related to a campus and innovation district, whereas the innovation district has the highest impact on the level of patenting. The science (business) park, also seemed positively related to the number of patents, but population size influenced this relation, which caused an exogeneity. While the number of science parks do have a positive impact on the patents within a municipality, there is no role of a science park on the level of patenting in neighbouring municipalities, neither does the type of science park has influence on this. So to answer the research question, science parks in the Netherlands positively influence innovation within a municipality, but they do not affect innovation in neighbouring municipalities.

7. Discussion

The outcomes of the research imply that a science park contributes to the innovation within a municipality, but not in neighbouring municipalities. First, this can be linked to theory of clustering whereas Marshall (2013) states that agglomeration economies are a driver for companies to cluster together due to localisation economies. In the case of science parks, companies are attracted to the principle of 'knowledge in the air' at which companies benefit from the local knowledge spillovers. Second, besides the theory of agglomeration, the findings are also comparable with the proximity theory of Boschma (2005). The findings about the type of science parks insinuate that organizational proximity matters. In organizational proximity, partners find the relevant organizational similarities that help them to work together, which is beneficial for interactive learning. The collaboration between universities, academic centres, companies and R&D facilities at the science (business) park, campus and innovation district confirm the impact on the level of patenting within a municipality. However, the relation between the science (business) park and the level of patents is influenced by the population size. The knowledge of the science (business) parks is best transmitted via face-to-face interaction, which occurs when there is social proximity, so in this case not caused by organizational proximity. Cities are drivers for a high social proximity as there is a lot of face-to-face interaction and thus a lot of knowledge exchange (Feldman and Kogler, 2010). The exact reason behind why population size influences the relation between science (business) parks and patenting, and not the relation of a campus or an innovation district, is unclear, as more research needs to be done to substantiate the correlation. A possible explanation could be that science (business) parks rather tend to locate at places close to cities because e.g., it is a more attractive place for businesses due to closeness to the market or that universities are more situated in cities, as a university is crucial for the collaboration within a science park. Third, the outcome that science parks do not influence the level of patenting in neighbouring municipalities, can be linked to the scholars that state innovation is hard to spillover through space. Knowledge tend to cluster at the science parks where R&D facilities and skilled labour are important. The outcomes disprove that knowledge of a science park can reach other regions and that it positively affects the patenting levels in neighbouring municipalities (Botazzi and Peri, 2003). While Magionni, Nosvelli and Uberti (2007) found that clusters influence the neighbouring territories through a trickling down process of spatial diffusion, this is not the case for science parks in the Netherlands. Science parks can be linked to the theory of clustering but is not a cluster as science parks are often based on policy intervention and subsidies, while clusters emerge naturally (le Duc and Lindeque, 2017). This distinction would declare why clusters influence the innovation in neighbouring municipalities, while with science parks the knowledge sticks within the municipality. A declaration could be that the knowledge at science park is complex and rather sticky. Tacit knowledge is spatially sticky, difficult to create and thus harder to spillover to regions outside of its production (Balland and Rigby, 2016). Another explanation could be that there is not an optimal technological distance between the municipality and the neighbouring municipality, which is necessary for knowledge to spillover (Moreno, Paci and Usai, 2005). Additional research is needed to reveal if the type of knowledge plays a role in the non-spatial effect of science parks, or if there are other factors that influence why neighbouring municipalities do not profit from the proximity to a science park.

This research is relevant for the scientific literature as is fills in the gap about the relation between a science park and innovation within a municipality and neighbouring municipalities. From the literature, questions are posed to what extent science parks influence the levels of patenting within a municipality, and whether and to what extent the proximity of a science park contributes to innovation in neighbouring municipalities. The outcomes proof that municipalities achieve greater innovation by hosting a science park. However, the concentration of the high innovative activity does not trickle down to neighbouring municipalities. This research is a stepping-stone for further research to elaborate on the relation between science parks and innovation in neighbouring municipalities and what might change in order to make a spatial spillover possible.

The societal relevance relies in the recommendations for policy implications. Science parks do affect the level patents, and are therefore a success for boosting innovation within a municipality. The more science parks a municipality has, the higher the impact, although, one science park also influences the level of patents substantially. So, setting up a science park is a way to boost innovation within a municipality and enable participation in the global knowledge economy. The type of science park that results into the highest innovation output is the innovation district. So, if a municipality wants to boost innovation, the innovation district is the most beneficial. The other type that influences the level of patents is a campus while setting up a science (business) park in higher populated areas is not beneficial, as it does not affect the patenting output. If a municipality wants to boost innovation within the region, via a trickling down process to the neighbours, setting up a science park is not the way to reach this goal. Therefore, there is a misunderstanding among the policy makers that science parks do affect the innovation within the region, nor does the type of science park has an impact on patenting. Based on the theory, there are ways for policy makers to enable knowledge spillovers through space by e.g. investing in the infrastructural network and sectors that are related to the knowledge produced at the science park, but to clarify if these steps are affecting the level of patenting in neighbouring municipalities, further research is necessary.

There are several caveats that can be placed aside this research. The first one is that the data of the dataset is imprecise. At the end of the trajectory, it came to notice that there was an inconstancy between the observations and the exact number of municipalities in the Netherlands. Within the dataset, 782 municipalities are included, while in 2020 the Netherlands consist of 355 municipalities. This inconstancy is related to the merge of municipalities, while the old municipalities were still included within the dataset. This was caused by the source of the population data (Statline, 2021), because this dataset referred to the municipalities with the name they had in a certain year, and referred to the new name when merged the next year, while the dataset of the patents (OECD Patent Quality Indicators database, 2021)(OECD REGPAT database, 2021) is based on the names of the municipalities in 2020. This flaw in the dataset, led to do a robustness check in order to see the impact. The robustness check is a poison regression, which handles the count data better than a linear regression. The regression shows (see appendix B1), that the variables Total_SP, campus and innovation district are insignificant, while in the regression in figure 12, these variables are significant. This implies that unreliability of the research, as the dataset is incorrect.
A second downside of this research, as a consequence of the incorrect dataset, is that the spatial regression is only focused on the year 2018. It was not possible to make a weighted variable of the science parks and type of science parks for every year as R gave an error because the municipalities in 2018 did not have the same number as the municipalities in previous years. However, it was chosen to still make a spatial regression of the best-represented year, to give an idea of the relation between science parks and patenting in neighbouring municipalities. Though, these results cannot be generalized for the Netherlands from 1980-2020 as it only gives an impression of the spatial relation in 2018.
The third pitfall has to do with the classification of the typologies science (business) park, campus and innovation district. From the theory, distinctions between the typologies arose, but from the dataset of the Knowledge location QGIS file of all the clusters within the Netherlands, it was unclear when the maker classified something as a science (business) park or as a campus. In some cases, it even looks like the maker based the typology on the name as the TU/e campus has the typology campus, while Leiden Bio Science Park is typed as science (business) park, but the difference between them is unclear. In further research, it is important to make clearer distinctions between the different typologies in the dataset and to be more transparent about the considerations naming something a science (business) park, campus and innovation district.

While the incorrect dataset hugely affects the outcomes of the research, it is still an interesting topic, which gives some impressions about the relation between science parks and innovation within municipalities and neighbouring municipalities. This research combines the different theories on geography of innovation, cluster theories and (spatial) knowledge spillovers, and shed some new lights on the issues around the topic of science parks and innovation. Unless the outcomes are unreliable, this research could be a stepping stone for further investigations on the concepts of science parks and their impact on innovation within regions. As already addressed, some of the relations within the research could be investigated more. One of the suggestions is to look for explanatory variables that influence the higher positive impact of the innovation district on the patenting data. Another suggestion would be to investigate why science (business) parks are influenced by the population size, and campus and innovation district are not. The last suggestion for a more in depth declaration of the results would be to investigate if technological proximity and infrastructure have impact on the spatial knowledge spillovers of science parks to neighbouring municipalities. A suggestion for new research would be to investigate the relation between science parks and the level of breakthroughs within municipalities and neighbouring municipalities.

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Appendix A: Formation of the dataset

1. Formulating the quality indicator

The quality indicator is recoded into low, medium and high according to the medians of the indicator quality_index_4

1st Qu: 0.18
Median: 0.24
3rd Qu: 0.32

Quality_index_4 <= 0.18 = Low
Quality_index_4 > 0.18 & quality_index_4 <= 0.32 = Medium
Quality_index_4 > 0.32 = High

2. Renaming of the municipalities

In order to merge the patenting data to the population data, it is crucial that the municipality names match. In some cases, this was not the case, so the municipalities needed to be renamed in order to have the exact same name.

's-Gravenhage (gemeente) = ’s-Gravenhage
Groningen (gemeente) = Groningen
Utrecht (gemeente) = Utrecht
Beek (L.)= Beek
Laren (NH) = Laren
Middelburg (Z) = Middelburg
Rijswijk (ZH.) = Rijswijk
Stein (L) = Stein

Hengelo (O) → Hengelo
Hengelo (GLD) → Deleted, as it does not exists

Noardeast-Fryslân → Noardeast-FryslÃ¢n
Súdwest Fryslân → SÃºdwest-FryslÃ¢n

3. Included and excluded science parks

Figure 15: Included science parks

Municipality name	Name of science park	Type of science park	Year
Arnhem	Arnhems Buiten (Energy Business Park)	Science (business) park	1931
Arnhem	Industriepark Kleefse Waard	Science (business) park	1945
Eindhoven	TU/e Campus	Campus	1956
Hilversum	Hilversum Media Park	Science (business) park	1963
Son en Breugel	Bedrijvenpark Ekkersrijt	Science (business) park	1980
Wageningen	Business & Science Park Wageningen	Science (business) park	1980
Enschede	Kennispark Twente	Campus	1982
Leiden	Leiden Bio Science Park	Science (business) park	1985
Delft	Delftechpark	Science (business) park	1995
Amsterdam	Amsterdam Science Park	Science (business) park	2002
Eindhoven	High Tech Campus Eindhoven	Campus	2003
Delft	TU Delft Science Park	Science (business) park	2005
Leeuwarden	WaterCampus Leeuwarden	Campus	2005
Sittard-Geleen	Brightlands Chemelot Campus	Campus	2006
Eindhoven	Strijp-S Eindhoven	Innovation district	2006
Wageningen	Wageningen Campus	Campus	2006
Terneuzen	Biopark Terneuzen	Science (business) park	2007
Helmond	Automotive Campus	Campus	2008
Breda	Triple O Campus	Campus	2008
Maastricht	Brightlands Maastricht Health Campus	Campus	2009
Rotterdam	RDM Campus Rotterdam - Rotterdam Makers District	Campus	2009
Woensdrecht	Business Park Aviolanda	Science (business) park	2010
Noordwijk	Space Business Park	Science (business) park	2010
Leeuwarden	Dairy Campus	Campus	2011
Utrecht	Utrecht Science Park	Science (business) park	2011
Venlo	Brightlands Campus Greenport Venlo	Campus	2012
Groningen	Campus Groningen	Campus	2012
Noordoostpolder	Dyntes Tech Park	Science (business) park	2012
Helmond	Food Tech Brainport	Science (business) park	2012
Nijmegen	Mercator Science Park - BV Campus	Science (business) park	2012
Oss	Pivot Park	Science (business) park	2012
Zwolle	Polymer Science Park	Science (business) park	2012
Hilversum	Werf35	Science (business) park	2012
Delft	Biotech Campus Delft	Campus	2013
Zoetermeer	Dutch Innovation Park	Science (business) park	2013
Nijmegen	Novio Tech Campus	Campus	2013
Alkmaar	Energy Innovation Park	Science (business) park	2014
Hengelo	High Tech Systems Park	Science (business) park	2014
Rotterdam	M4H Rotterdam - Rotterdam Makers District	Campus	2014
's-Hertogenbosch	SPARK Campus	Campus	2014
Amsterdam	VU Campus	Campus	2014
's-Hertogenbosch	Grow Campus	Campus	2015
Noordenveld	Health Hub Roden	Science (business) park	2015
Veldhoven	Health Innovation Campus	Campus	2015
Amsterdam	Knowledge Mile	Innovation district	2015

Figure 16: Excluded science parks

Municipality name	**Name of science park**	**Type of science park**	**Year**
Eindhoven	Strijp-S Eindhoven	Innovation hotspot	2006
Amsterdam	A LAB	Innovation hotspot	2013
The Hague	The Hague Security Delta- HSD Campus	Innovation hotspot	2014
Tilburg	Midpoint Center for Social Innovation Tilburg	Innovation hotspot	2014
Amsterdam	De Ceuvel	Innovation hotspot	2014
Amsterdam	B. Amsterdam	Innovation hotspot	2014
Amsterdam	Knowledge Mile	Innovation hotspot	2015
Rotterdam	Plant one Rotterdam	Innovation hotspot	2015

Appendix B: Innovation within municipalities

1. Poisson regression

Figure 17: Poisson regression with dependent variable Total_patents

Independent variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Total_SP	-0.034 (0.041)			
Science_business_park		0,153* (0.074)	-0.101 (0.088)	-0.099 (0.141)
Campus		0.017 (0.082)	-0.072 (0.060)	-0.075 (0.143)
Innovation_district		-0.143 (0.111)	-0.352 (0.106)***	
Population_size			0.000004*** (0.0000008)	0.000001 (0.000004)
Density			0.00003 (0.0001)	-0.0003 (0.0001)
Quality_index_mean				0.025 (0.026)
Observations	8163	8163	5113	2145
Adjusted R^2	0.919	0.919	0.936	0.379

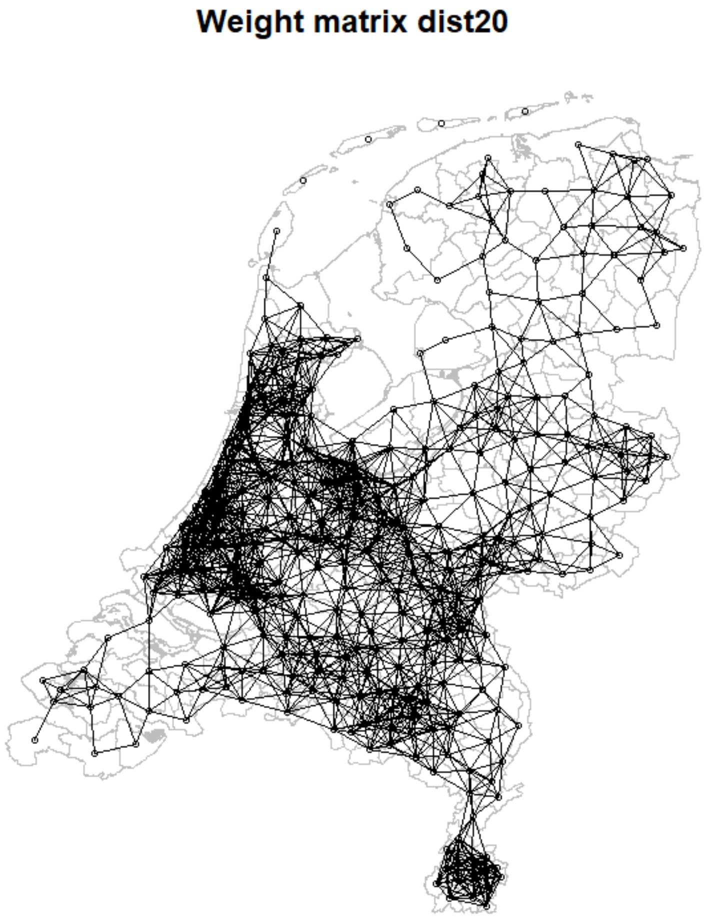
*p<0.05; **p<0.01; ***p<0.001

Appendix C: Innovation in neighbouring municipalities

1. Weight distance matrix

```
summary(wDist20, zero.policy= TRUE)

Characteristics of weights list object:
Neighbour list object:

Number of regions: 355
Number of nonzero links: 1852

Percentage nonzero weights: 1.46955
Average number of links: 5.216901

2 regions with no links
92 221

Link number distribution:

 0  1  2  3  4  5  6  7  8  9 10 11 12 18

 2  6  8 39 75 91 57 39 19 10  6  1  1  1

6 least connected regions:
100 101 125 273 284 344 with 1 link

1 most connected region:

256 with 18 links

Weights style: W

    Weights constants summary:

      n     nn  S0       S1       S2

    W 353 124609 353 148.6064 1469.514
```

Figure 18: Weight distance matrix based on 20km



2. Moran test

> moran.test(SPshp2018$csum_count,wDist20, zero.policy = TRUE)
Moran I test under randomisation

data: SPshp2018$csum_count
weights: wDist20 n reduced by no-neighbour observations

Moran I statistic standard deviate = -1.0677, p-value = 0.8572
alternative hypothesis: greater
sample estimates:

Moran I statistic	Expectation	Variance
-0.038541828	-0.002840909	0.001117983

3. LMtest

```
model: lm(formula = SPshp2018$count_nbr.x ~ SPshp2018$csum_count + lagmatrixSP)

weights: wDist20


       statistic parameter p.value
LMerr  0.9214945         1  0.3371
LMlag  0.9116978         1  0.3397
RLMerr 0.0128450         1  0.9098
RLMlag 0.0030482         1  0.9560
SARMA  0.9245427         2  0.6299
```

```
model: lm(formula = SPshp2018$count_nbr.x ~ SPshp2018$csum_sbp + LagmatrixSBP +
SPshp2018$csum_camp +LagmatrixCAMP + SPshp2018$csum_innd + LagmatrixINND +
SPshp2018$Population.size + SPshp2018$Density)

weights: wDist20


       statistic parameter p.value
LMerr    1.60306         1 0.20547
LMlag    0.48327         1 0.48695
RLMerr   2.87219         1 0.09012 .
RLMlag   1.75240         1 0.18558
SARMA    3.35546         2 0.18680
```

4. Error model

Call: spautolm(formula = reg18.5, listw = wDist20, zero.policy = TRUE)

Residuals:

Min	1Q	Median	3Q	Max
-246.7119	-6.8844	4.9432	7.6225	1584.5673

Regions with no neighbours included:
210 367

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.1973	9.5020	-0.4417	0.6587
SPshp2018$csum_count	91.5623	13.9371	6.5697	5.042e-11
lagmatrixSP	29.6766	30.4941	0.9732	0.3305

Lambda: -0.082583 LR test value: 0.93735 p-value: 0.33296

Numerical Hessian standard error of lambda: 0.084966

Log likelihood: -1384.435
ML residual variance (sigma squared): 13646, (sigma: 116.82)
Number of observations: 224
Number of parameters estimated: 5
AIC: 2778.9
Nagelkerke pseudo-R-squared: 0.16255

Call: spautolm(formula = reg18.6, listw = wDist20, zero.policy = TRUE)

Residuals:

Min	1Q	Median	3Q	Max
-605.5529	-16.2954	-6.6971	5.0719	605.3227

Regions with no neighbours included:
91 210 367

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.5820e+01	7.9155e+00	3.2620	0.001106
SPshp2018$csum_sbp	-1.5267e+01	1.6759e+01	-0.9110	0.362309
LagmatrixSBP	1.4021e+01	3.6231e+01	0.3870	0.698767
SPshp2018$csum_camp	1.1931e+02	1.7872e+01	6.6762	2.453e-11
LagmatrixCAMP	1.3735e+01	3.7012e+01	0.3711	0.710562
SPshp2018$csum_innd	1.1116e+03	6.6685e+01	16.6692	< 2.2e-16
LagmatrixINND	-1.0467e+02	1.1389e+02	-0.9190	0.358083
SPshp2018$Population.size	-6.3245e-04	9.3919e-05	-6.7340	1.651e-11
SPshp2018$Density	9.2308e-03	5.4395e-03	1.6970	0.089697

Lambda: -0.098616 LR test value: 1.4878 p-value: 0.22256

Numerical Hessian standard error of lambda: 0.080184

Log likelihood: -1235.96
ML residual variance (sigma squared): 5747.5, (sigma: 75.812)
Number of observations: 215
Number of parameters estimated: 11
AIC: 2493.9
Nagelkerke pseudo-R-squared: 0.65569

5. Lag model

Call:lagsarlm(formula = reg18.5, listw = wDist20, zero.policy = TRUE)

Residuals:

Min	1Q	Median	3Q	Max
-247.6976	-5.3841	5.1079	7.2798	1584.4130

Type: lag
Regions with no neighbours included:
210 367

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-3.9695	10.1360	-0.3916	0.6953
SPshp2018$csum_count	92.0971	13.9428	6.6053	3.966e-11
lagmatrixSP	39.0557	32.9399	1.1857	0.2358

Rho: -0.08519, LR test value: 0.97631, p-value: 0.32311

Asymptotic standard error: 0.084186

z-value: -1.0119, p-value: 0.31157

Wald statistic: 1.024, p-value: 0.31157

Log likelihood: -1384.416 for lag model
ML residual variance (sigma squared): 13642, (sigma: 116.8)
Nagelkerke pseudo-R-squared: 0.1627
Number of observations: 224
Number of parameters estimated: 5
AIC: 2778.8, (AIC for lm: 2777.8)
LM test for residual autocorrelation
test value: 0.33105, p-value: 0.56504

Call:lagsarlm(formula = reg18.6, listw = wDist20, zero.policy = TRUE)

Residuals:

Min	1Q	Median	3Q	Max
-609.9726	-16.5534	-7.3029	4.2676	609.9726

Type: lag
Regions with no neighbours included:
91 210 367

Coefficients: (numerical Hessian approximate standard errors)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.6452e+01	8.4796e+00	3.1195	0.001812
SPshp2018$csum_sbp	-1.4233e+01	1.6966e+01	-0.8389	0.401522
LagmatrixSBP	1.1127e+01	3.8557e+01	0.2886	0.772896
SPshp2018$csum_camp	1.1914e+02	1.7948e+01	6.6385	3.170e-11
LagmatrixCAMP	1.1205e+01	3.9710e+01	0.2822	0.777823
SPshp2018$csum_innd	1.1091e+03	6.6922e+01	16.5736	< 2.2e-16
LagmatrixINND	-1.9590e+01	1.0883e+02	-0.1800	0.857149
SPshp2018$Population.size	-6.2368e-04	9.4354e-05	-6.6101	3.841e-11
SPshp2018$Density	8.3620e-03	5.5646e-03	1.5027	0.132913

Rho: -0.059125, LR test value: 0.52454, p-value: 0.46891

Approximate (numerical Hessian) standard error: 0.077789

z-value: -0.76006, p-value: 0.44722

Wald statistic: 0.57769, p-value: 0.44722

Log likelihood: -1236.442 for lag model
ML residual variance (sigma squared): 5784, (sigma: 76.053)
Nagelkerke pseudo-R-squared: 0.65415
Number of observations: 215
Number of parameters estimated: 11
AIC: 2494.9, (AIC for lm: 2493.4)