The Impact of Co-Inventor Networks on Smart Cleantech Innovation: The Case of Montreal Agglomeration

Ekaterina Turkina 1,*, and Boris Oreshkin 2

1 Department of Entrepreneurship and Innovation, HEC Montreal, Montreal, QC H3T 2A7, Canada
2 Unity Technologies, Montreal, QC H3K 1G6, Canada; boris.oreshkin@mail.mcgill.ca
* Correspondence: ekaterina.turkina@hec.ca

Abstract: We use patent big data and apply a combination of network analysis techniques to explore the social structure of the Montreal tech community and its embeddedness in the global innovation landscape. In particular, we focus on the smart cleantech segment. In doing so, we analyze the effect of inventor collaborations on innovations and the emergence of smart clean technologies and smart sustainable solutions in Montreal and their global impact. Our analysis reveals the importance of both local and international ties for the general development of innovations in Montreal’s competitive urban economy, with a stronger impact of international ties, in generating smart cleantech innovations. We discuss the implications of our findings for smart cleantech and cleantech clusters and for further development of tech agglomerations.

Keywords: smart cleantech; industrial clusters; co-inventor networks

1. Introduction

Scholars have demonstrated that industrial and knowledge activities are increasingly localized in specific geographic locations [1,2], because firms are no longer self-sufficient in terms of innovation, and their performance is becoming increasingly conditioned by their ability to absorb information and knowledge from their peers [3–11]. Analyzing this co-localization dynamics, researchers speak about the development of learning clusters, or regional innovation hubs (some researchers also use the term ecosystems), where firms, universities, regional authorities and for-profit and not-for-profit research institutions collaborate together and share resources, knowledge and expertise on a variety of joint projects [12–17]. Researchers also increasingly speak about the phenomenon of cluster connectivity [18–20] where it is important for co-located firms not only to collaborate with their peers inside their respective clusters, but also increasingly across clusters, in order to access complementary pools of knowledge and expertise.

It has been argued that co-localization and also cross-cluster linkages are particularly vibrant and intense in technology-intensive industries where innovation is the main source of competitive advantage [21]. Modern industries, and in particular, high-tech industries and clusters are going through the so-called Industry 4.0 revolution. The rise of Industry 4.0 (known as the trend towards automation and data exchange in manufacturing technologies and processes which include cyber-physical systems (CPS), the internet of things (IoT), industrial internet of things (IIOT), cloud computing, cognitive computing and artificial intelligence, deep learning and neural networks in particular [22]) is an important transformation that makes it possible to collect and analyze big data from a variety of devices and create systems capable of learning and adjusting to new market needs, thereby enabling firms to produce goods of higher quality at lower costs due to more flexible, rapid and efficient processes [23]. This manufacturing revolution is projected to increase efficiency, enhance industrial growth, and introduce significant changes to the labor market, and as a consequence, change the competitiveness of firms and locations [24]. Another
important consequence of Industry 4.0 revolution is that it is projected to alleviate stress on the environment by giving a boost to smart cleantech innovations.

Cleantech is a highly agglomerated sector, in which cleantech clusters are located in a few cities [25] and then these clusters participate in the International Cleantech Network that helps to promote different types of international partnerships and collaborations between them (https://www.internationalcleantechnetwork.com/ accessed on 9 June 2021). Cleantech implies a diverse range of products and technologies that aim at exploiting renewable materials and resources and creating significantly less emissions and waste than conventional solutions [26,27]. It is important to differentiate between “cleantech” and “green”, because cleantech has a strong focus on developing technologies to mitigate environmental challenges and reduce ecological footprint. These technologies are predominantly interdisciplinary, as they often include artificial intelligence algorithms, IoT, IIOT, cloud computing, and other elements of Industry 4.0. Therefore, innovation efforts for value creation in the cleantech sector are sustainability-driven [25] and cleantech solutions are usually called disruptive innovations, since they often include Industry 4.0 technologies and have a game-changing impact on economies and the environment [28]. At the same time, the term “green” is a broader term and can include developments in any sector or firm that tries to conduct its operations in a more sustainable or environmentally-friendly manner.

Cleantech is an emerging and fairly recent, but highly agglomerated and highly connected sector. While there has been considerable research in management on sustainability and recent technical research related to clean technologies, the literature on industrial clustering provides very few studies of cleantech clusters. Therefore, the major research question of this paper is to understand how the local and global connectivity affect the performance of cleantech clusters and influence regional cleantech innovations overtime. This question is important not only for the literature on clusters, but also for understanding the developments in this highly important sector that has a strong potential to positively influence sustainability of the whole ecosystem and improve our environment and our living.

To answer this research question, this paper interacts with several strands of literature such as the literature on cluster connectivity [18–20], industrial studies of smart cleantech [25] and emerging literature on co-inventor networks [29,30] to develop a conceptual framework on the role of co-inventor networks in shaping innovation from smart cleantech agglomerations. The paper then tests the hypotheses issuing from this theoretical framework by applying longitudinal network perspective to the analysis of Montreal tech agglomeration with a specific focus on smart cleantech innovations. Montreal has been chosen as a testing ground for this paper due to the fact that it hosts several strong tech agglomerations such as the Montreal Techno ICT cluster, Écotech Quebec which focuses on the development of sustainable solutions, and Montreal AI, artificial intelligence cluster, which has been recognized as one of the leading hubs globally.

The paper looks into the structure of the social fabric of the Montreal tech community with a particular focus on smart cleantech patents. It analyzes network linkages between smart cleantech co-inventors and examines how local and global collaboration ties affect the quality of Montreal smart cleantech innovations. It also explores forward citations of Montreal smart cleantech patents and evaluates how Montreal’s smart cleantech innovations are embedded in a global cleantech community. The paper concludes with broader perspectives for regional participation in cleantech advancements, as well as regional innovation and regional environmental development.

The rest of the paper is organized as follows. The next section presents the theoretical overview of the literature on clusters and social networks and relates this to smart cleantech developments. This section also develops hypotheses to be tested in the empirical part of the paper. The following section presents important contextual information on Montreal tech agglomeration. It is followed by the empirical section that visualizes Montreal smart cleantech innovations and their global embeddedness and tests the hypotheses developed
in the theoretical part of the paper. The following section provides discussion of findings and the last two sections provide conclusions and discussion of research limitations and directions for future work.

2. Network View of Innovation in Industrial Clusters

Researchers who study industrial clusters argue that firms locate in clusters to obtain numerous benefits such as access to important information and knowledge from their peers, as well as access to the advanced pool of talent and other resources such as funding, favorable policies and developed infrastructure [1,2,31]. There are multiple studies that show that there are positive spillovers from locating in industrial clusters for firm innovation [32].

At the same time, there is a growing literature that argues that these positive spillovers in are not given, and sheer physical colocation and geographic proximity is not sufficient to produce beneficial externalities. It has been argued that positive spillovers and positive impact on innovation happen in the process of complex interactions among an ecosystem’s agents [4,33–37]. There is extensive research that demonstrates that the structure of local social relationships has an important effect on the ecosystem’s economic performance and innovation [14,38–40]. For instance, Hervas-Oliver and Albors-Garrigos [41] analyzed the leading European ceramic tile cluster and discovered that there is a synergistic effect from the interaction between a firm’s internal and relational resources. In similar vein, Turkina et al. [42] argued that it is important to look at the interplay between cluster-level and firm-level factors to explain firm innovation in clusters. For instance, they find that intra-cluster social networks help to avoid the downturns in firm innovation due to cluster characteristics, in case clusters are overspecialized or too broad. Scholars generally argue that the exchange of tacit knowledge requires direct contact [31]. Therefore, they have focused on local linkages between firms and examined them as key channels through which co-located firms exchange knowledge and innovate, thereby creating positive effects for regional economic growth [43]. Bathelt et al. [44] called this phenomenon “local buzz”.

At the same time, researchers also speak about different non-geographical types of proximity [3] such as organizational, cognitive or technological proximity [45–48], where an organization can learn from other organizations regardless of geographical distance. Therefore, recent research argues that in addition to local connections, external connections can also be a strong factor for knowledge spillovers when distant partners share some non-geographical proximities and establish linkages [44,49]. In establishing distant linkages and tapping into distant locations, local firms not only enrich their knowledge and advance their competences [50–53], but in doing so they also help to advance the local ecosystem [54–56]. Thus, existing studies indicate that more distant linkages and linkages spanning international borders are important and effective in bringing in external knowledge to local ecosystems [57,58], a phenomenon called “global pipelines” [44]. Recent empirical studies have demonstrated that more distant and international linkages are important in embedding local ecosystems in the global knowledge and innovation system and helping local clusters avoid complacency and lock in [20,33,59].

Moreover, there are studies that argue that collaborations between firms that do not necessarily share any proximities can also be beneficial, because this can help recombine information and knowledge and come up with radical innovations. For instance, Turkina and Van Assche [40] found out that more radical innovations in the Bangalore tech hub emerged as the result of formal inter-firm cooperation between firms from different technological communities.

While cluster literature has mostly focused on inter-firm linkages, industrial clusters are also linked by a variety of other important linkages that can be critical for innovation. For instance, Tödtling et al. [60] explored different interaction channels and innovation spillovers and provided evidence that, depending on the sector, informal contacts via conferences, fairs, and labor turnover could also be important innovation links between different regional innovation systems. Colovic [19] examined links between clusters as
entities, typically in the form of inter-cluster alliances, and argued that inter-cluster alliances enable a greater number of different organizations to benefit from cross-cluster partnerships.

Another important linkage overlooked by the cluster literature is linkages between co-inventors. Studying co-inventor networks would be even more important in understanding innovation in industrial clusters, as they are directly linked to innovation [29], while interorganizational linkages often represent relationships of a more transactional or market-based nature (e.g., buyer-supplier relationships or relationships with firm clients [61,62]). Similarly, informal linkages between people and formal cluster alliances are extremely important for cluster collaboration and mobilization, but they do not always have a direct effect on innovation output.

Linkages between inventors located in different clusters, but collaborating on joint patents, can serve as important channels for knowledge transfer into the local milieu and for exchange of best innovation practices. However, the literature on co-inventor networks has mostly been concerned with the analysis of such networks at the level of specific industries in particular countries, such as the Chinese pharmaceutical industry [63], with the analysis of their structural properties [64], with the determinants of co-inventor tie formation [65], with modeling tie-formation in specialized versus diversified cities [66], or with problems of detecting rising technology stars in such networks [67]. There are very few studies that chose to analyze how local and global co-inventor linkages contribute to innovation in industrial clusters, and how local co-inventor networks in industrial clusters are embedded in global networks. These shortcomings partly occur due to the need to process large data volumes in order to visualize and analyze such large-scale networks, as well as to apply specific network techniques.

At the same time, emerging studies in this direction give preliminary indication that co-inventor linkages may have an important effect on innovation. For instance, Lubango [29] studied the impact of international co-inventor ties on the emergence of green innovations measured by patents in green industry at the country level in Brazil, South Africa and India and found positive effects of international links on the development of green innovations, especially in Brazil and India where co-inventor networks tend to be bigger.

Nevertheless, subnational differentiation and analysis at the level of industrial clusters is important because tech innovations have a tendency to concentrate in urban centers and locational dynamics and local linkages are also important to take into consideration. Many competitive urban economies comprise agglomerations in several tech industries that are also highly linked globally [68]. Disruptive innovations such as smart cleantech solutions require a re-combination of different types and pools of knowledge because they are at the edge of several tech disciplines, and producing these innovations needs a combination of different competences. Hervas-Oliver et al. [69] explored radical innovation in Marshallian industrial districts and found that the introduction of technology-distant knowledge and new firms from different (to the focal) industries were necessary mechanisms for generating innovation. They also found access to leading incumbents’ networks, based on social norms, to be another important factor.

Given the discussion above, global linkages between inventors in tech fields such as smart cleantech allow for access to external knowledge and allow local scientists to quickly follow global advancements in this fast developing sector. At the same time, local linkages are important due to their capacity to share tacit knowledge, as discussed above. Based on this discussion, we develop the following hypothesis:

**Hypothesis 1 (H1):** Smart cleantech will show a significant concentration of local linkages, and also the presence of strong international linkages.

At the same time, we can expect that the structure of collaborations in smart cleantech will be different from that of other industries since this sector is highly concentrated in a few urban localities [70], because smart cleantech solutions are developed at the crossroads of several disciplines such as energy, artificial intelligence, ICT, electrical engineering, etc.
and because they usually emerge in competitive urban economies with high firm and inventor concentrations in several tech industries, in other words, they emerge in urban locations that host several advanced tech clusters. Therefore, it is possible to expect that local industrial clusters will significantly shape the structure of the global network in smart cleantech, as global linkages will primarily be between these localities. Similarly, we can expect the geography of innovations in smart cleantech to be shaped by this factor. Moreover, the existing literature argues that public policy also plays a role in fostering collaborative networking [71,72]: cleantech being a rather regulated sector affected by public policies, cleantech clusters around the world show the presence of strong cluster associations (such as Écotech Quebec in Montreal) who in collaboration with policymakers try to influence the growth and competitiveness of local cleantech. Therefore, it is logical to expect that the global geography of co-inventor networks will be strongly influenced by the presence of strong cleantech clusters. Based on this discussion, we develop the following hypothesis:

**Hypothesis 2 (H2):** The geography of the global co-inventor network and innovation in smart cleantech will be different from that in other industries as it will be strongly shaped by smart cleantech clusters.

The literature on co-inventor networks argues that there is a direct link between active participation in co-inventor collaboration and innovation output, as well as the quality of innovation. Inventors who are involved in many collaborations have important access to boundary-spanning knowledge that is critical for producing new innovations [30,73]. At the same time, as in the case with inter-firm network literature, the literature on co-inventor networks differentiates between local and global linkages and argues that both are important for innovation. Local linkages help with tacit knowledge transfers and enable local social capital and trust that facilitate cooperation and positively influence innovation output and quality. At the same time, global linkages give access to pockets of different and complementary knowledge and enable local inventors to revise their usual innovation practices and develop creative solutions that are not typical of their local milieu [29]. Based on this discussion, we develop the following two hypotheses:

**Hypothesis 3 (H3):** There is a positive association between participation in local co-inventor networks and smart cleantech innovations in competitive urban economies.

**Hypothesis 4 (H4):** There is a positive association between participation in global co-inventor networks and smart cleantech innovations in competitive urban economies.

3. Context: Montreal Tech Agglomeration

We have chosen to focus on Montreal as our testing ground due the fact that the city hosts several important tech clusters such as Montreal AI, Montreal Techno and Écotech Quebec.

The Montreal AI cluster comprises firms working on artificial intelligence technologies, while the Techno Montreal cluster includes firms working in ICT, telecommunication, and electronics sectors. Écotech Quebec is a cluster in clean technologies.

Montreal’s Techno cluster hosts over 5000 firms and relevant organizations and is ranked third in ICT industry in North America for job growth (https://numana.tech/en/industry/ accessed on 6 June 2021). Montreal’s AI sector even though being young, already boasts over 450 firms and various research institutions and laboratories and has been frequently referred to as the second global AI hub after Silicon Valley (https://www.montrealinternational.com/en/news/montreal-is-2nd-global-artificial-intelligence-hub/, accessed on 6 June 2021). At present, the Montreal AI ecosystem is composed of over 300 innovative local firms and many multinational giants as the city has attracted an unprecedented number of global high-tech firms that opened their AI labs in Montreal.
The Écotech Quebec cluster focuses specifically on the development of clean technologies and regroups approximately a thousand organizations linked to cleantech. Over 70% of those cleantech firms are active in international markets. They provide over 30,000 jobs and boast total revenues of over $11 billion (https://www.montrealinternational.com/en/news/montreal-is-2nd-global-artificial-intelligence-hub/ accessed on 6 June 2021). The Quebec cleantech sector is well positioned with strong assets, high levels of human capital, and strong expertise in many cleantech sub-sectors.

It is also important to note government efforts to support Montreal tech agglomeration. The Canadian government has recognized the importance of the growing AI and cleantech sectors for Canadian economy and made considerable investments in these fields. For example, Montreal’s Scale AI business consortium received $230 million from the government (https://www.scaleai.ca/290-million-in-support-for-scale-ai-the-ai-powered-supply-chains-superccluster/ accessed on 6 June 2021). The Government of Québec has also made “a $60 million financial contribution to support the activities of Scale AI and its IVADO LABS laboratory, an organization created to provide support and guidance to companies in implementing projects developed as part of the supercluster” (https://www.scaleai.ca/290-million-in-support-for-scale-ai-the-ai-powered-supply-chains-superccluster/ accessed on 6 June 2021). Additionally, Montreal universities received over $250 million for research in Industry 4.0. Moreover, the governments of Canada and Quebec have recently contributed over $3 million for the development of clean technologies related to electric smart transportation and Quebec also invested nearly $13 million in cleantech projects across the province (https://betakit.com/quebec-rda-invests-nearly-13-million-in-30-cleantech-projects-across-the-province/ accessed on 6 June 2021). Additionally, Federal government invested around $8 million in Quebec cleantech (https://www.canadianmanufacturing.com/manufacturing/feds-invest-7-8m-in-quebec-cleantech-198427/ accessed on 6 June 2021).

4. Data and Description of Variables

4.1. General Dataset Description

We downloaded big data for approximately 7.5 million patents from the USPTO API issued between 1976 and 2021 (https://patentsview.org/apis/api-endpoints/patents accessed on 6 June 2021). The following fields for each patent are used in the analysis:

- patent id
- inventor id
- inventor latitude
- inventor longitude
- inventor country
- patent date
- cooperative patent classification—patent CPC group code (four characters)
- citing patent id
- citing patent date
- citing inventor id
- citing inventor latitude
- citing inventor longitude
- citing inventor country

4.2. Innovation

There is an extensive literature that argues that the use of raw patent count is not an accurate approach to innovation as the same weight is given to some very important patents as well as to only marginally important patents [74,75]. Existing research argues that patent citations are a better measure of innovation than raw patent count, because they reflect the quality and the impact of innovation and the value of the invention for the global community [7,50,76]. To the best of our knowledge, there are no studies analyzing
the effects of co-inventor networks on the quality of innovation—patent citations—in industrial clusters.

For a given patent, we calculate the number of forward citations in a 10 year window. Therefore, the number of citations for each patent is equal to the number of patents citing this patent whose date falls within a 10 year period from date of the given patent. Furthermore, each patent is geo-located using the coordinates of its inventors provided by the USPTO database. We define the greater Montreal area as a square with lower left corner with coordinates 45.34386984223199, −74.03047374768484 and upper right corner 45.78207414941647, −73.29255948538957. Consequently, inventors falling within this square are considered to be Montreal based inventors. Between 1976 and 2020, there were 19,396 Montreal patents. The total number of inventors of these patents is 10,293.

The total number of citations of Montreal patents within the 10 year window is 81,743.

Next, we focus on patents in smart cleantech. In order to select these patents, we use specific codes that refer to such patents as suggested by the literature [77]. We focus on patents in smart clean technologies such as energy efficient computing and communication technologies; smart grid technologies, smart technologies for efficient electrical power generation, transmission or distribution; load management and smart metering; e-mobility, efficient engines, smart vehicles; climate change mitigation ICT technologies in buildings, etc. These patents are located in the Y category of CPC classification. Filtering all the patents to obtain smart cleantech patents gave us 463 such patents in Montreal. We also calculated the number of forward citations in a 10 year window for such patents.

4.3. Citation Networks and Co-Inventor Networks

The network analysis is based on the graphs defined by edges and vertices. Throughout the analysis we define a vertex to be a geolocated patent inventor. USPTO database provides latitude and longitude for each inventor, which we convert to Mercator projection for visualization purposes. We follow the USPTO convention and each inventor is given a unique id based on their disambiguated name and patent id. Note that the same person can have multiple unique ids (and associated geographical locations) corresponding to the actal geographical locations where their patents were invented. For citation networks, an edge in the graph is created between every inventor of a given patent and every inventor of respective citing patents. In collaboration networks, for each patent, edges are created between all distinct pairs of inventors of this patent. If a patent has a single author this is counted as a single edge between the author and him/herself. The nodes are overlaid over the Mercator map projection according to their coordinates. The edges between nodes are represented by bundled edge curves that are computed by Hurter, Ersoy and Telea algorithm [78]. The purpose of edge bundling is to reveal the detailed substructure of the graph, which becomes visible after edge bundling. Data processing is accomplished on two HP ProLiant DL580 G7 servers, each equipped with four Intel Xeon E7-4870 2.4GHz 10-core processors and 256 GB of RAM. The data processing software stack includes Ubuntu 18.04, python, dask (parallel computation engine [79]) and HoloVis and Datashader (python visualization tools https://holoviz.org, accessed on 6 June 2021).

5. Analysis

The right column in Figure 1 presents Montreal smart cleantech patents, and the left column presents Montreal patents in other fields.
Figure 1. Geographic visualization of local co-inventor networks.

Figure 1 indicates very few patents in smart cleantech between 1980–1990 and considerable growth in such patents in the following decades. We can also observe that overtime the network becomes denser and more established. An interesting feature of the cleantech network compared to the other-fields-network is that, unlike downtown Montreal which is very central in other industries, most of the smart cleantech collaborations seem to happen on the South shore (to the right of the St-Lawrence river), which is logical given that many cleantech firms are located there.
Next, we visualize global collaborations occurring between Montreal inventors and inventors from other countries. Figure 2 presents these visualizations. The right column presents collaborations considering only smart cleantech patents, while the left column presents collaborations considering Montreal patents in other fields.

Figure 2 indicates that Montreal has diverse international collaborations both in cleantech and other industries and we also see that such collaborations grow and diversify considerably over time. At the same time, there are some obvious differences with regards
to smart cleantech where collaborations are most intense with North America and Continental and Nordic Europe, whereas in other industries we also see strong collaborations with Asia, the UK, Australia and South America. This result is logical, given a limited number of advanced cleantech clusters, most of them locating in Canada, the US, and Northern and Continental Europe, according to the International Cleantech Cluster Network (https://www.internationalcleantechnetwork.com/who-our-members-are accessed on 6 June 2021). Moreover, if we zoom in on the localities with which Montreal smart cleantech collaborates, it becomes evident that these are urban locations such as Paris or Stockholm.

Next, we visualize the share of local and international linkages in the Montreal tech hub (Figure 3).

Next, we move to modeling citation networks and Figure 4 presents the geographic distribution of Montreal patent citations. The right column presents the citations of smart cleantech patents, while the left column presents citations in other fields.
Figure 4 indicates similar patterns for smart cleantech and citations in other industries. Montreal patents have become more cited by the global community over time and not just in North America and Europe, where most of the citations were at the beginning, but also in other parts of the world, and especially Asia. It is possible to say that the impact of Montreal’s cleantech innovations has grown over time. At the same time, it is important to note important differences in citation networks. While other Montreal patents are well cited in Australia, Eastern Europe and Latin America, Montreal smart cleantech patents
receive very few citations from these locations. Moreover, zooming in on citation networks makes it clear that Montreal is mostly cited by inventors located in urban centers with strong cleantech clusters. Most of the citations for Montreal cleantech come from localities such as Stockholm and Copenhagen in Europe, and Boston, Phoenix, San Diego, San Jose in North America, all with vibrant cleantech clusters.

Taken together with the findings regarding the geography of co-inventor networks, it is possible to say that the findings support our second hypothesis that the structure of smart cleantech citation and collaboration networks will be different from other industries and will be shaped by the presence of smart cleantech clusters.

Next, in order to test the effect of local and global co-inventor networks on patent citations, we conduct a negative binomial regression, which is efficient regarding count data, and unlike Poisson regression does not rely on the mean-variance equality restriction. We operationalize local linkages with the number of local inventors. We operationalize the international linkages with the binary variable, which is zero when no international collaborators participate as patent inventors and one otherwise. We control for the decade, as previous visualizations have indicated that both patents and citations significantly increase over time. The first regression focuses on smart cleantech patents and their citations, while the second regression takes into consideration patents in other fields in Montreal and all their citations. Table 1 presents the results of the analysis.

|                  | Patent Citations for Montreal Smart Cleantech | Patent Citations for Montreal Patents in Other Fields |
|------------------|-----------------------------------------------|------------------------------------------------------|
|                  | coefficients and standard errors              | coefficients and standard errors                      |
| Local linkages   | −0.005                                        | 0.01 ***                                             |
|                  | (0.008)                                       | (0.002)                                              |
|                  | 0.27 **                                       | 0.32 ***                                             |
|                  | (0.10)                                        | (0.03)                                               |
|                  | 0.30 ***                                      | 0.37 ***                                             |
|                  | (0.05)                                        | (0.01)                                               |
| International linkages |                                       |                                                      |
| Decade           | 0.30 ***                                      | 0.37 ***                                             |
|                  | (0.05)                                        | (0.01)                                               |
| N                | 463                                           | 7928                                                 |
| LR chi2 (3)      | 39.77                                         | 1080.19                                              |
| Prob > chi2      | 0.0000                                        | 0.0000                                               |
| Log likelihood   | −1493.4611                                    | −25,841.515                                          |
| Pseudo R2        | 0.01                                          | 0.02                                                 |

*** and ** denote significance at the 1%, 5% and 10% levels, respectively.

Table 1 indicates that both models are highly significant and presents interesting results. When Montreal patents and their citations in fields other than smart cleantech are taken together, we see that both local and international linkages are positive and highly significant, whereas in the case of smart cleantech patents, local linkages are insignificant, while international linkages are positive and significant. In both models the coefficient for international linkages is bigger than that of the local (the test of difference in coefficients confirms a statistically significant difference in coefficients). Taken together, these results indicate that, while overall local collaboration is important, international collaborations give stronger effect on innovation. At the same time, the importance of international collaborations is even more important in the case of smart cleantech, while local collaborations are not as important as for innovations in other industries. Therefore, these results confirm our fourth hypothesis and do not confirm our third hypothesis. Nevertheless, it is important to note that local links are significant and positive for innovation in sectors other than cleantech in the competitive urban economy.
6. Discussion of Findings

Our analysis revealed that both local and global co-inventor collaborations had a positive and significant influence on innovations across different clusters located in Montreal. These findings are generally in line with the existing economic geography literature that argues that both local buzz and global pipelines are important for innovation [44,51].

At the same time, in the case of smart cleantech patents, only international linkages turned out to be significant. This may be explained by the fact that smart cleantech that uses Industry 4.0 elements represents some of the most advanced radical innovations existing in the tech sphere, and therefore such innovations may often require a combination of different and distant knowledge pools and competences. It is also important to note that while local linkages turned out to be not that important for Montreal smart cleantech innovations, the concentration of local collaborations in smart cleantech has again been on the rise since 2000. This may be due to the policies undertaken by the local and federal governments aimed at strengthening the local cleantech cluster, as well as Écotech Quebec cluster association that explicitly fosters local collaborations. These results are in line with the literature that argues that public policy and public innovation intermediaries (such as Écotech Quebec) play an important role in shaping collaborative networking among individuals, firms and organizations [71,72].

At the same time, given the importance of long-range ties and access to different pools of knowledge, as well as the presence of other advanced tech hubs in Montreal such as Montreal Techno and Montreal AI, an important policy implication would be to foster those inter-hub collaborations, as well as collaborations with other global cleantech hubs. Data visualizations of patent citations clearly indicate that Montreal smart cleantech is gaining significant importance internationally as Montreal patents are increasingly cited all over the world. Enhancing more long-range collaborations would allow Montreal smart cleantech to have even stronger impact on the global cleantech community. This can also be a good lesson for other smart cleantech clusters, as well as clusters in other fields that demand cutting-edge innovations and are at the crossroads of several disciplines, such as robotics clusters, etc.

These results contribute to the emerging research in economic geography and innovation in collocated clusters, cluster networks and global inter-cluster relationships [43,68,80]. This paper demonstrates that in addition to inter-firm networks [81], informal contacts [60], and formal alliances between clusters [19], local and global co-inventor networks can be important factors affecting innovation in industrial clusters and broader competitive urban economies composed of multiple clusters.

These findings are also interesting for those researchers who study smart cleantech more specifically [25] as, essentially, our analysis reveals that this sector is strongly shaped by the presence of clusters, and at the same time, knowledge flows in this sector (as demonstrated by the citation network) are essentially global. Therefore, innovation in this sector demands both access to localities where smart cleantech expertise is strong, and also access to diverse international pools of knowledge.

Finally, this paper also extends the recent and rising literature on co-inventor networks [29,30] and demonstrates that they are not only relevant in specific industrial settings, but are also an important factor in cluster innovation dynamics.

Methodologically, our analysis also responds to Glückler and Doreian’s [82] call to use more sophisticated network analysis techniques and visualizations to study economic geography and innovation phenomena. The network algorithms and methods that we used to portray co-inventor and patent citation networks could be further used in the economic geography and cluster literature to visualize collaboration and innovation patterns across clusters, industries and countries. Additionally, big data techniques that we used to filter patents and assign patents and inventors to specific geographic coordinates can be helpful for researchers in further exploring both co-inventor and inter-firm networks at a large scale.
7. Conclusions

This paper contributes to several streams of literature such as that on clusters and connectivity [18,20,44,51,81], on co-inventor networks [29,30] and smart cleantech [25]. It analyzes the impact of co-inventor networks on innovation from industrial clusters in a new and rapidly advancing cleantech sector. It also compares the impact of co-inventor networks in cleantech with other industries using the competitive urban economy of Montreal as its testing ground. To date, few empirical studies explored the potential impact of co-inventor networks on the performance of clusters and urban economies composed of several clusters, especially with regards to innovation. With a database comprising over 19,000 patents and over 80,000 citations, the results give a good indication of the positive interplay between co-inventor networks and innovation in the competitive urban economy.

This paper also largely responds to the call by Lazzeretti et al. [83] to rethink clusters and move towards a new research agenda for cluster research. While our results indicate that the global geography of co-inventor networks and the evolution of such networks over time in tech fields such as smart cleantech are largely shaped by the presence of strong industrial clusters, co-inventor networks can overtime affect the development trajectories and performance of industrial clusters, because our analysis demonstrated that global connectedness plays a crucial role in cluster innovation, especially in such cutting edge fields as smart cleantech. Therefore, co-inventor linkages should be considered as an important variable by researchers exploring cluster evolution and innovation.

8. Research Imitations and Directions for Future Work

It is important to note several research limitations. First our analysis focuses only on one tech hub, Montreal, and future studies could apply our methodology and evaluate whether our results hold across localities by analyzing a global network of co-inventor linkages and patent citations. Second, our analysis focuses on co-inventor networks, while the literature also mentions inter-firm linkages as an important factor for innovation. Future studies could use a multiplex network approach by overlaying co-inventor networks with inter-firm networks and studying the interplay between the two in their impacts on cluster and regional innovations. Third, it would be interesting to analyze co-inventor networks in more detail with regards to gender, ethnicity, education and other inventor characteristics and examine how such characteristics affect innovation in industrial clusters and localities in the presence of several industrial clusters. Finally, future studies could also apply different approaches to measuring innovation. As discussed above, using patents as a proxy for innovation involves important drawbacks as many patented inventions have no or marginal economic value and quite a short market life. We tried to address this by using patent citations that indicate the value of a patent for other inventions, other than raw patent counts. At the same time, there are other approaches to measuring innovation, such as using patent family size [84] as a proxy of patent value or using other indicators such as trademarks [85–87]. Future studies could use these other measures and compare across different measures for better assessment of the innovation phenomenon. Finally, researchers could also use other social relationship measures to assess if other types of connectivity matter for smart cleantech innovations.

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References
1. Malmberg, A.; Maskell, P. Localized Learning Revisited. Growth Chang. 2006, 37, 1–18. [CrossRef]
2. Maskell, P.; Malmberg, A. Localised learning and industrial competitiveness. Camb. J. Econ. 1999, 23, 167–185. [CrossRef]
3. Boschma, R. Proximity and Innovation: A Critical Assessment. Reg. Stud. 2005, 39, 61–74. [CrossRef]
4. Boschma, R.A.; Ter Wal, A.L.J. Knowledge Networks and Innovative Performance in an Industrial District: The Case of a Footwear District in the South of Italy. Ind. Innov. 2007, 14, 177–199. [CrossRef]
5. Cortright, J. Making Sense of Clusters: Regional Competitiveness and Economic Development; Discussion Paper; Brookings Institution Metropolitan Policy Program: Washington, DC, USA, 2006.
6. Chesbrough, H. Open Business Models: How to Thrive in the Innovation Landscape; Harvard Business School Press: Boston, MA, USA, 2006.
7. Frost, S.T. The Geographic Sources of Foreign Subsidiaries’ Innovation. Strateg. Manag. J. 2001, 22, 101–123. [CrossRef]
8. Granstrand, O.; Bohlin, E.; Oskarsson, C.; Sjöberg, N. External Technology Acquisition in Large Multi-technology Corporations. R D Manag. 1992, 22, 111–133. [CrossRef]
9. Hervas-Oliver, J.L.; Albors-Garrigos, J.; de-Miguel, B.; Hidalgo, A. The role of a firm’s absorptive capacity and the technology transfer process in clusters: How effective are technology centres in low-tech clusters? Entrep. Reg. Dev. 2012, 24, 523–559. [CrossRef]
10. Singh, J. Collaborative networks as determinants of knowledge diffusion patterns. Manag. Sci. 2005, 51, 756–770. Available online: http://www.jstor.org/stable/20110371 (accessed on 5 June 2021). [CrossRef]
11. Lane, P.J.; Lubatkin, M. Relative absorptive capacity and interorganizational learning. Strateg. Manag. J. (UK) 1998, 461–477. Available online: https://onlinelibrary.wiley.com/doi/10.1002/(SICI)1097-0266(199805)19:5%3C461::AID-SMJ953%3E3.0.CO;2-L (accessed on 5 June 2021).
12. Asheim, B.T. Learning Regions as Development Coalitions: Partnership as Governance in European Workfare States? Concepts and Transformation. Int. J. Action Res. Organ. Renew. 2001, 6, 73–101.
13. Delgato, M.; Porter, M.E.; Stern, S. Clusters, convergence, and economic performance. Res. Policy 2014, 43, 1785–1799. [CrossRef]
14. Giuliani, E. Network dynamics in regional clusters: Evidence from Chile. Res. Policy 2013, 42, 1406–1419. [CrossRef]
15. Giuliani, E.; Bell, M. The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. Res. Policy 2005, 34, 47–68. [CrossRef]
16. Porter, M. On Competition; Harvard Business School Press: Boston, MA, USA, 1998; Available online: https://www.hbs.edu/faculty/Pages/item.aspx?num=34977 (accessed on 29 June 2021).
17. Porter, M. The economic performance of regions. Reg. Stud. 2003, 37, 549–578. [CrossRef]
18. Bathelt, H.; Glückler, J. The Relational Economy: Geographies of Knowing and Learning; Oxford University Press: New York, NY, USA, 2011.
19. Colovic, A. Cluster connectivity and inter-cluster alliance portfolio configuration in knowledge-intensive industries. M@n@gement 2019, 22, 619–635.
20. Turkina, E.; Van Assche, A. Global connectedness and local innovation in industrial clusters. J. Int. Bus. Stud. 2018, 49, 706–728. [CrossRef]
21. Rothaermel, F. Chapter 7 Competitive advantage in technology intensive industries. In Technological Innovation: Generating Economic Results (Advances in the Study of Entrepreneurship, Innovation & Economic Growth, Volume 18); Gary, D., Marie, L., Thursby, C., Eds.; Emerald Group Publishing Limited, Bradford: West Yorkshire, UK, 2008; pp. 201–225.
22. Wang, B.; Tao, F.; Fang, X.; Liu, C.; Liu, Y.; Freiheit, T. Smart Manufacturing and Intelligent Manufacturing: A Comparative Review. Engineering 2020, 2020, 1, 167–185. [CrossRef]
23. Frank, A.G.; Dalenogare, L.S.; Ayala, N.F. Industry 4.0 technologies: Implementation patterns in manufacturing companies. Int. J. Prod. Econ. 2019, 210, 15–26. [CrossRef]
24. Sima, V.; Gheorghe, I.G.; Subi’, J.; Nancu, D. Influences of the Industry 4.0 Revolution on the Human Capital Development and Consumer Behavior: A Systematic Review. Sustainability 2020, 12, 4035. [CrossRef]
25. Aagaard, A.; Saari, U.A.; Mäkinen, S.J. Mapping the types of business experimentation in creating sustainable value: A case study of cleantech start-ups. J. Clean. Prod. 2021, 279, 123182. [CrossRef]
26. Cumming, D.; Henriques, I.; Sadorsky, P. ‘Cleantech’ Venture Capital Around the World; International Review of Financial Analysis; Elsevier: Poland, The Netherlands, 2016; Volume 44, pp. 86–97.
27. Giudici, G.; Guerin, M.; Rossi-Lamastra, C. The creation of cleantech startups at the local level: The role of knowledge availability and environmental awareness. Small Bus. Econ. 2019, 52, 815–830. [CrossRef]
28. Vaidya, S.; Ambad, P.; Bhosle, S. Industry 4.0—A Glimpse. Procedia Manuf. 2018, 20, 223–238. [CrossRef]
29. Lubango, L.M. Effects of international co-inventor networks on green inventions in Brazil, India and South Africa. J. Clean. Prod. 2020, 244, 118791. [CrossRef]
30. Talmooresnejad, L.; Beaudry, C. The importance of collaborative networks in Canadian scientific research. Ind. Innov. 2018, 25, 1-40. [CrossRef]
31. Storper, M.; Venables, A.J. Buzz: Face-to-face contact and the urban economy. J. Econ. Geogr. 2004, 4, 351–370. [CrossRef]
32. Lai, Y.-L.; Hsu, M.-S.; Lin, F.-J.; Chen, Y.-M.; Lin, Y.-H. The effects of industry cluster knowledge management on innovation performance. J. Bus. Res. 2014, 67, 734–739. [CrossRef]
33. Crespo, J.; Suiire, R.; Vicente, J. Network structural properties for cluster long-run dynamics: Evidence from collaborative R&D networks in the European mobile phone industry. Ind. Corp. Chang. 2015, 25, 261–282. [CrossRef]
34. Dyer, J.; Singh, H. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. Acad. Manag. Rev. 1998, 23, 660–679. [CrossRef]
35. Giuliani, E. The selective nature of knowledge networks in clusters: Evidence from the wine industry. J. Econ. Geogr. 2006, 7, 139–168. [CrossRef]
36. Huggins, R.; Thompson, P. A Network-based view of regional growth. J. Econ. Geogr. 2013, 14, 511–545. [CrossRef]
37. Täube, F.A.; Karna, A.; Sonderegger, P. Economic geography and emerging market clusters: A co-evolutionary study of local and non-local networks in Bangalore. Int. Bus. Rev. 2019, 28, 101496. [CrossRef]
38. Morrison, A.; Rabellotti, R. Knowledge and Information Networks in an Italian Wine Cluster. Eur. Plan. Stud. 2009, 17, 983–1006. [CrossRef]
39. Saxenian, A. The New Argonauts: Regional Advantage in a Global Economy; Harvard University Press: Cambridge, UK, 2006.
40. Turkina, E.; Van Assche, A. An Anatomy of Bengaluru’s ICT Cluster: A Community Detection Approach. Manag. Organ. Rev. 2019, 15, 533–561. [CrossRef]
41. Hervas-Oliver, J.L.; Albors-Garrigos, J. The role of the firm’s internal and relational capabilities in clusters: When distance and embeddedness are not enough to explain innovation. J. Econ. Geogr. 2009, 9, 263–283. [CrossRef]
42. Turkina, E.; Oreshkin, B.; Kali, R. Regional innovation clusters and firm innovation performance: An interactionist approach. Reg. Stud. 2019, 53, 1193–1206. [CrossRef]
43. Owen-Smith, J.; Powell, W. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. Organ. Sci. 2004, 15, 5–21. [CrossRef]
44. Bathelt, H.; Malmberg, A.; Maskell, P. Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. Prog. Hum. Geogr. 2004, 28, 31–56. [CrossRef]
45. Gilsing, V.; Nooteboom, B.; Vanhaverbeke, W.; Duysters, G.; Oord, A.V.D. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. Res. Policy 2008, 37, 1717–1731. [CrossRef]
46. Nooteboom, B. Inter-Firm Alliances: Analysis and Design; Routledge: London, UK, 1999.
47. Nooteboom, B.; Van Haverbeke, W.; Duysters, G.; Gilsing, V.; Van den Oord, A. Optimal cognitive distance and absorptive capacity. Res. Policy 2007, 36, 1016–1034. [CrossRef]
48. Rigby, D.L. Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. Reg. Stud. 2015, 49, 1922–1937. [CrossRef]
49. Lorenzen, M.; Mudambi, R. Clusters, Connectivity and Catch-up: Bollywood and Bangalore in the Global Economy. J. Econ. Geogr. 2013, 13, 501–534. [CrossRef]
50. Almeida, P.; Phene, A. Subsidiaries and knowledge creation: The influence of the MNC and host country on innovation. Strat. Manag. J. 2004, 25, 847–864. [CrossRef]
51. Bathelt, H.; Li, P.-F. Global cluster networks—Foreign direct investment flows from Canada to China. J. Econ. Geogr. 2013, 14, 45–71. [CrossRef]
52. Hagedoorn, J.; Duysters, G.G. External Sources of Innovative Capabilities: The Preferences for Strategic Alliances or Mergers and Acquisitions. J. Manag. Stud. 2002, 39, 167–188. [CrossRef]
53. Schilling, M.A.; Phelps, C.C. Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. Manag. Sci. 2007, 53, 1113–1126. [CrossRef]
54. Arora, A.; Gambardella, A. The Globalization of the Software Industry: Perspectives and Opportunities for Developed and Developing Countries. Innov. Policy Econ. 2005, 5, 1–32. [CrossRef]
55. Karnia, A.; Täube, F.; Sonderegger, P. Evolution of Innovation Networks across Geographical and Organizational Boundaries: A Study of R&D Subsidiaries in the Bangalore IT Cluster. Eur. Manag. Rev. 2013, 10, 211–226. [CrossRef]
56. Wolfe, D.A.; Gertler, M.S. Clusters from the Inside and Out: Local Dynamics and Global Linkages. Urban Stud. 2004, 41, 1071–1093. [CrossRef]
57. Patibandla, M.; Petersen, B. Role of Transnational Corporations in the Evolution of a High-Tech Industry: The Case of India’s Software Industry. World Dev. 2002, 30, 1561–1577. [CrossRef]
58. Pietrobelli, C.; Rabellotti, R. Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? World Dev. 2011, 39, 1261–1269. [CrossRef]
59. Narula, R. Innovation systems and ‘inertia’ in R&D location: Norwegian firms and the role of systemic lock-in. Res. Policy 2002, 31, 795–816. [CrossRef]
Sustainability 2021, 13, 7270

60. Todtling, F.; Lehner, P.; Trippl, M. Innovation in knowledge intensive industries: The nature and geography of knowledge links. *Eur. Plan. Stud.* **2006**, *14*, 1035–1058. [CrossRef]

61. Alcacer, J.; Oxley, J. Learning by supplying. *Strat. Manag. J.* **2014**, *35*, 204–223. [CrossRef]

62. Dyer, J.H.; Chu, W. The Determinants of Trust in Supplier-Automaker Relationships in the U.S., Japan and Korea. *J. Int. Bus. Stud.* **2000**, *31*, 259–285. [CrossRef]

63. Perri, A.; Scarf, V.G.; Mudambi, R. What are the most promising conduits for foreign knowledge inflows? innovation networks in the Chinese pharmaceutical industry. *Ind. Corp. Chang.* **2017**, *26*, 333–355. [CrossRef]

64. Newman, M.E.J. Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality. *Phys. Rev. E* **2001**, *64*, 016132. [CrossRef] [PubMed]

65. Cassi, L.; Plunket, A. Research Collaboration in Co-inventor Networks: Combining Closure, Bridging and Proximities. *Reg. Stud.* **2013**, *49*, 936–954. [CrossRef]

66. Van der Wouden, F.; Rigby, D. Co-inventor networks and knowledge production in specialized and diversified cities. *Reg. Sci. Policy* **2019**, *56*, 1833–1853. [CrossRef]

67. Zhu, L.; Zhu, D.; Wang, X.; Cunningham, S.; Wang, Z. An integrated solution for detecting rising technology stars in co-inventor networks. *Scientometrics* **2019**, *121*, 137–172. [CrossRef]

68. Turkina, E.; Van Assche, A.; Doloreux, D. How co-located clusters interact? Evidence from the case of Greater Montreal. *J. Econ. Geogr.* **2020**, *20*, 75–93. [CrossRef]

69. Hervás-Oliver, J.-L.; Albornos-Garrigos, J.; Estelles-Miguel, S.; Boronat-Moll, C. Radical innovation in Marshallian industrial districts. *Reg. Stud.* **2017**, *52*, 1388–1397. [CrossRef]

70. Tvedt, H.L. The formation and structure of cleantech clusters: Insights from San Diego, Dublin, and Graz. *Nor. Geogr. Tidskr. Nor. J. Geogr.* **2019**, *73*, 53–64. [CrossRef]

71. Rossi, F.; Calofoli, A.; Colovic, A.; Russo, M. Public Innovation Intermediaries and Digital Co-Creation. Research Contribution to the OECD TIP Co-Creation Project. 2020. Available online: https://stip.oecd.org/stip/knowledge-transfer/case-studies (accessed on 5 June 2021).

72. Rossi, F.; Calofoli, A.; Russo, M. Networked by design: Can policy requirements influence organisations’ networking behaviour? *Technol. Forecast. Soc. Chang.* **2016**, *105*, 203–214. [CrossRef]

73. Uzzi, B.; Spiro, J. Collaboration and Creativity: The Small World Problem. *Am. J. Sociol.* **2005**, *111*, 447–504. [CrossRef]

74. Archibugi, D. Patenting as an indicator of technological innovation: A review. *Sci. Public Policy* **1992**, *19*, 357–368. [CrossRef]

75. Cohen, W.M.; Levinthal, D. Innovation and Learning: The Two Faces of R&D. *Econ. J.* **1989**, *99*, 569. [CrossRef]

76. Cantwell, J.A.; Mudambi, R. Physical attraction and the geography of knowledge sourcing in multinational enterprises. *Glob. Strat. J.* **2011**, *1*, 206–232. [CrossRef]

77. EU Patent Office. Finding Sustainable Technologies in Patents. 2021. Available online: https://e-courses.epo.org/pluginfile.php/1238/mod_resource/content/4/sustainable_technologies_brochure_en.pdf (accessed on 5 June 2021).

78. Hurter, C.; Ersoy, O.; Telea, A. Graph bundling by Kernel Density Estimation, EUROVIS 2012. In Proceedings of the Eurographics Conference on Visualization, Vienna, Austria, 7 May 2012; pp. 865–874. [CrossRef]

79. Rocklin. Dask: Parallel Computation with Blocked algorithms and Task Scheduling. In Proceedings of the 14th Python in Science Conference. 2015. Available online: https://conference.scipy.org/proceedings/scipy2015/pdfs/matthew_rocklin.pdf (accessed on 5 June 2021).

80. Lu, R.; Ruan, M.; Reve, T. Cluster and co-located cluster effects: An empirical study of six Chinese city regions. *Res. Policy* **2016**, *45*, 1984–1995. [CrossRef]

81. Barthelt, H.; Zhao, J. Conceptualizing multiple clusters in mega-city regions: The case of the biomedical industry in Beijing. *Geoforum* **2016**, *75*, 186–198. [CrossRef]

82. Gluckler, J.; Doreian, P. Editorial: Social network analysis and economic geography—positional, evolutionary and multi-level approaches. *J. Econ. Geogr.* **2016**, *16*, 1123–1134. [CrossRef]

83. Lazzeretti, L.; Capone, F.; Calofoli, A.; Sedita, S.R. Rethinking clusters. Towards a new research agenda for cluster research. *Eur. Plan. Stud.* **2019**, *27*, 1879–1903. [CrossRef]

84. Kabore, F.; Park, W. Can patent family size and composition signal patent value? *Appl. Econ.* **2019**, *51*, 6476–6496. [CrossRef]

85. Flikkema, M.; Castaldi, C.; De Man, A.P.; Seip, M. Explaining the Trademark-Innovation Linkage: The Role of Patents and Trademark Filing Strategies. *Acad. Manag. Proc.* **2015**, *15*, 16624. [CrossRef]

86. Flikkema, M.; De Man, A.-P.; Castaldi, C. Are Trademark Counts a Valid Indicator of Innovation? Results of an In-Depth Study of New Benelux Trademarks Filed by SMEs. *Ind. Innov.* **2014**, *21*, 310–331. [CrossRef]

87. Mendonça, S.; Pereira, T.; Godinho, M.M. Trademarks as an indicator of innovation and industrial change. *Res. Policy* **2004**, *33*, 1385–1404. [CrossRef]