An agent-based simulation approach to the facilitated industrial symbiosis in the presence of trust: NISP dataset

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A Thesis

In

The Department

Of

Mechanical and Industrial and Aerospace Engineering

Presented in Partial Fulfillment of the Requirements
For the Degree of Master of Applied Science (Industrial Engineering) at

Concordia University
Montreal, Quebec, Canada

April 2018

CONCORDIA UNIVERSITY
School of Graduate Studies

This is to certify that the thesis prepared

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Entitled: An agent-based simulation approach to the facilitated industrial symbiosis in the presence of trust: NISP dataset

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Industrial Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract:

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Pollution is one of the most important challenging political and social issues of our day. Reducing or eliminating pollution and solid waste is a critical issue. Hence the current awareness about the environment encourages citizens, governments, and corporations to take drastic measures to minimize their environmental footprints. Industrial Symbiosis (IS) network is a subfield of Industrial Ecology which tries to develop exchanges between firms in order to reduce waste and material use. The goal is to encourage trading relationships between firms (networks) to avoid waste disposal to the environment. Ideally, these exchanges can also reduce or eliminate the use of new materials and reduce energy use. In our research, we use agent-based simulation to analyze how these networks function and what motivates firms to engage in industrial symbiosis (IS) networks. Active exchanges between firms are referred to as network synergy. We also evaluate the specific environmental benefits of these IS exchanges. We use these results to determine how existing IS networks can be improved and how new IS networks can be developed. Using a sensitivity analysis, we evaluate the impact of parameters changes to the level of material exchanges and environmental impacts in the IS network. In addition to parameters commonly modeled for IS exchanges such as the distance between firms, participation in IS information sessions, the similarity of waste streams, and landfill cost, we modeled the level of trust in the network and the impact of taxation for landfill use or avoidance. Significantly, our results indicate that increasing trust within the network has a significant effect on increasing synergy in the network. We tested our idea by using a large dataset from the National Industrial Symbiosis Program (NISP) network. NISP was a facilitated industrial symbiosis program in the UK from 2003 to 2012. We base our results on five geographic regions of the NISP network.

ACKNOWLEDGEMENT

Foremost, I would like to express my sincere gratitude to my supervisor Professor Ketra Schmitt for the continuous support of my master study and research. Her guidance helped me in all the time of research and writing of this thesis.

Besides my supervisor, I would like to thank the rest of my thesis committee Professor Ali Akgunduz for his patience, motivation, enthusiasm, hard questions and immense knowledge and Professor Raymond Paquin for his encouragement and insightful comments.

Nobody has been more important to me in the pursuit of this project than the members of my family. I would like to thank my parents Azam Sobhani and Mohammadhassan Danyali, for giving birth to me at the first place and supporting me spiritually and financially in whatever I pursue. They are the ultimate role models. I wish to thank my Sister Elham Danyali for her endless love and support throughout my life.

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3 Introduction

Various strategies exist to reduce pollution and material use, ranging from efforts at the household level such as reuse and recycling, industrial efforts to capture pollution streams prior to release into the environment and regulatory efforts to develop markets to cap allowable emissions and trade emission rights and to remediate existing pollution. In spite of these efforts, the need to develop new methods to avoid pollution and improve existing methods continues. Industries with easily recyclable waste products such as metal, glass, wood pulp, and paper have long reused scrap materials within their facilities. Municipalities have also set up recycling programs to reuse these materials post-consumer waste. These materials are not only easier to recycle, but they can be used instead of extracting new materials. This provides strong financial incentives for municipalities to encourage recycling and strong social incentives for individual households to participate. Some solid waste streams are more difficult to address. Large industrial sites are particularly impacted as they have large quantities of plastic waste, electronic waste, etc. Air and water emissions are also problematic. These can include natural and man-made contaminants as well as heat. The Canadian oil sands industry is a good example. Ingredients for a synthetic fuel are developed by extracting hydrocarbons from large quantities of sand in northern Alberta. This results in large quantities of scrap (solid waste), wastewater have been found to be one of the largest sources of air pollution. Fuel from Canadian oil sands is mainly used for transportation. Fossil fuel extraction is a major pollution source, and fossil fuel use is the primary cause of climate change. In Canada, the use of fossil fuel is expected to peak in 2019. While this thesis does not evaluate the potential of IS to address waste in the Alberta oil sands and fossil fuel industry, it does, in fact, provide an approach to use less energy as result of having less transportation in the IS network. The IS approach is of value to combatting climate change and pollution since using less fuel causes these industries to produce less energy and have less air pollution (Fletcher, 2017).

To make this point clearer, Canada produces 25 million tons of industrial waste per year(Tremonti, 2017). Even though different provinces in Canada has already started Industrial Symbiosis (IS) and Industrial ecology (IE) such as Bécancour industrial park in Quebec, Burnside in Nova Scotia, and, Acheson in Alberta but the term is not still well known in the country. Until recently, Quebec shipped most of its recyclable waste to China which had been one of the largest importers of recyclable waste. Starting in 2018, China has stopped importing waste, leaving Quebec and other regions with a crisis for waste recycling(Tremonti, 2017).While 40 percent of waste is recycled or reused within the province, Quebec must now find new ways to recycle 60 percent of its recyclable waste (D'Amours, 2017). IS approaches have the potential to reduce or even eliminate this waste stream. A closed-loop cycle is a system of industrial exchanges that has zero waste output, meaning that all waste has become an input stream within another firm.

Quebec now has both the incentive and opportunity to develop a closed-loop cycle to avoid industrial waste.

In this research, we evaluated the potential of industrial symbiosis (IS) networks to eliminate waste disposal from the industrial sector. Firms within networks exchange "materials, energy, water and/or by-products" between a group of firms (M. Chertow & Miyata, 2011). Symbiosis means living together according to the Oxford dictionary. In industrial symbiosis, this means firms can live together and survive from input that comes from others (Dictionary, n.d.). Industrial symbiosis is a subfield of Industrial Ecology (IE). Industrial ecology tries to change unwanted or waste material from one process into raw material for another. Industrial Symbiosis (IS) aim is to transform waste as outputs of a manufacturer into the input for another one (Davies, 2011). This can result in improvements in both economic and environmental condition. Environmental benefits could include landfill diversion, CO_2 reduction, etc. Facilitated industrial symbiosis helps the firms which are in the specific area to know each other and develop synergy.

In another view, we can see that the general level of trust in societies are decreasing(Harrington, 2017). Trust plays a vital role in society to enable individuals to engage in day-to-day life and solve problems collectively. Especially in industrial symbiosis, it helps firms to get closer together. Managers, by having more trust in their peers in the industrial sector can get closer to each other to do their synergy together. The finding of this research shows that the more trust in the network the more initiation, and therefore more willingness of the firms to join the network. By increasing the number of firms in the network the number of firms which continue their synergy will be more as well as the amount of landfill diversion and carbon reduction.

Problem:

After the Brundtland Commission and the decision of commitment to a sustainable environment in the world, the idea of industrial symbiosis is expanding, and Kalundborg is the first example of a well-function IS. The idea was to have an ecosystem in the industrial area. It describes the exchange of materials and by-products within the network (M. R. Chertow, 2007). Kalundborg has so many advantages, such as saving 3 million cubic meters of water by applying industrial symbiosis and doing synergy between firms (KalundborgSymbiosis Effective industrial symbiosisTitle, n.d.).

IS has been applied in several countries such as Australia, Austria, Brazil, Canada, China, Finland, India, Japan, Puerto Rico, the Netherlands, South Korea, Sweden, the UK, and the United States(Yap & Devlin, 2017).

In the UK specifically IS applies to a network which is called the National Industrial Symbiosis Program (NISP) which is developed in 2003 and it is an example of facilitated IS. The program started working in three regions at the beginning and then expand its work to the other regions of the UK. Our research is conducted based on the large dataset of this network.

By considering a large amount of waste production in Canada, IS needs to expand in this country as well. While industrial ecology is applied in Sarnia-Lambton region of Ontario(Bansal & Mcknight, 2000), but there is a need to have more IS sites as well as good policies to motivate firms to come into the network. The amount of waste disposal in Canada based on Statistics Canada was 25,103,034 in 2014 which is increased 1.7 percent compared to 2012. Quebec region specifically is the second largest producer of waste in the country, which was 5,714,630 in 2014, an increase of 2.3 percent from 2012. On the other hand, the diversion of waste is 9,057,177 which increased 7 percent from 2012 in the country and Quebec diverted 2,662,655 tons of waste on 2014 and it increased 6.2 percent from 2012(Canada, 2016). In Quebec they burn the wastes by inclinators which they invest the technological advance of the machine; however, the machines still produce CO_2 12 times more than the limit.

People agree about having no pollution, no wastes, healthier world, sustainable environment, etc. however, most of the ways which lead us to our utopia are either ignored or unknown. The reason could be because of the way that we describe the problem and decision of policies.

In our research, we considered several hypotheses:

A. More landfill Tax causes more initiation, completion, landfill diversion and Carbon reduction
B. More Carbon Tax causes more initiation, completion, landfill diversion and Carbon reduction
C. Less distance between firms causes more initiation, completion, landfill diversion and Carbon reduction
D. Less distance between firms and facilitators causes more initiation, completion, landfill diversion and Carbon reduction

E. Less aged wastes cause more initiation, completion, landfill diversion and Carbon reduction
F. More trust in the network causes more initiation, completion, landfill diversion and Carbon reduction

Based on this hypothesis we made an agent-based simulation model to test each of the hypothesis based on the real data that we have from NISP network.

This research design shows in the flowchart in figure 1.

4 Literature Review

IS networks exist throughout the world, and involve a wide range of industries including cement(Prosman, Wæhrens, & Liotta, 2017), iron and steel industry (Wu, Pu, Ma, Qi, & Wang, 2017), plastic(Dong et al., 2017), waste disposal, electronic wastes (Kangas & Seibel, 2018) and, heat and electricity production(Sokka, Lehtoranta, Nissinen, & Melanen, 2011). In some cases, Industrial Symbiosis networks have developed organically between firms. In order to encourage greater levels of material exchanges, several countries, provinces and municipalities have developed facilitated IS networks such as NISP in UK, Bécancour industrial park in Quebec (Karine MARKEWITZ, VERMETTE, & PINNA, 2008) and, some other programs in South Africa such as GISP, KISP and, WISP(Lyons, Basson, Nuwarinda, & Africa, 2017). In these networks, facilitators work with industries to identify potential exchanges and to help firms to find each other and develop relationships essential to these exchanges. We first review literature that focuses on IS networks that emerged within eco-industrial parks. These are industrial parks established using concepts from industrial ecology with the aim of creating more sustainable manufacturing. We next explore industrial symbiosis examples that emerged organically between firms.

Start

Literature Review

IS and Methodology Review

Logistic Regression Model to find the most important parameters

Significant parameters for initiation:

- Distance to NISP
- Landfill Diversion
- CO_2
- Cost Savings
- Age of waste
- Distance
- Distance to NISP-landfill Diversion
- Distance to NISP-Distance

Significant parameters for completion:

- Landfill Diversion
- CO_2
- Cost Savings
- Age of waste
- Distance

Agent-Based Simulation

Results:

- Increasing landfill tax has positive effects on completion percentage but negative effects on initiation, initiation and completion landfill diversion and carbon reduction
- Increasing Carbon tax has positive effects on completion percentage no significant effects on initiation, initiation and completion landfill diversion and carbon reduction
- Using less aged wastes has positive effects on completion and also landfill diversion and carbon reduction in completion stage no significant effects on initiation, initiation, landfill diversion and carbon reduction.
- Having less distance between two firms increases the number of completion, completion landfill diversion and carbon reduction and no significant effects on initiation, initiation, landfill diversion and carbon reduction.
- Having less distance between firms and NISP facilitator increases the number of completion, completion landfill diversion and carbon reduction and no significant effects on initiation, initiation, landfill diversion and carbon reduction
- Having more trust in the society has positive effects on initiation and completion percentage as well as landfill diversion and carbon reduction as a result of initiation and completion

priority	policies	advantage
1	Increasing trust in the network	1. Increasing either the number of the firms which come to the network or those that continue synergy or add additional wastes to the network 2. Increasing the amount of landfill diversion and carbon reduction
2	increasing Carbon tax	Increasing the initiation percentage. Carbon reduction and, landfill diversion increases in both stages.
3	increasing landfill tax	Increasing the initiation percentage, landfill diversion and carbon reduction in this stage.
4	Applying IS in a big city	Increasing the initiation and also landfill diversion and carbon reduction in initiation stage.
5	Applying IS in a small city	Increasing the completion and also landfill diversion and carbon reduction in completion stage.
6	Find a match as soon as possible to use a less aged waste in the network	Increasing the completion and also landfill diversion and carbon reduction in completion stage.

End

Figure 1: Flowchart which shows the flow of the thesis

Finally, we explore facilitated networks. In reviewing existing literature, our goal is to identify characteristics of successful material exchanges for specific firms and industries, and more generally, to understand what promotes successful IS networks.

Eco-town is a Japanese program for EIPs Established in 1997 by the Ministry of Environment Ministry of Economy, Trade, and Industry (METI) to promote landfill reduction. After 8 years, 47 recycling firms were built and 732,000 tons of landfill reduced from the environment. METI expanded the program to address a broader range of environmental problems such as global warming. In order to address global warming, METI established an eco-town in Kawasaki, an industrial city in Japan with numerous petrochemical and steel companies. By developing material exchanges within Kawasaki, several cement and construction firms began to replace a portion of virgin raw materials like limestone and coal with industrial by-products to produce Portland cement. They also used sewage sludge, slag, and surplus soil from construction sites, and soot dust and burnt residue as clay substitutes, while plastic wastes and waste tires were mainly used as fuel alternatives to coal. IS techniques allowed this industry to reduce CO_2 emissions by 43,000 tons per year and saved virgin raw materials.(Hashimoto, Fujita, Geng, & Nagasawa, 2010)

China is both the largest producer of iron and steel and the largest CO_2 emitter in the world. The iron and steel industry accounts for 10% of total domestic CO_2 emissions and is the third largest CO_2 emitter in China. This potential of CO_2 production makes this industry a target to meet for reducing emissions of CO_2. Yu et al. evaluated the CO_2 reduction in Integrated Steel Mills (ISMs). ISMs are critical industrial symbiosis networks, which combine production processes, large volumes of material, energy consumption, and potential connections with other actors in industrial systems. Yu et al. identified the three most effective symbiotic measures for CO_2 reduction are blast furnace gas (BFG) recycled on site as fuel and sold off-site, coke oven gas (COG) recycled on site as fuel and sold off-site, and blast furnace (BF) slag sold to the cement industry. Currently, using gaseous and solid byproducts is more beneficial than using sensible heat because of their influences on CO_2 reduction. The study also demonstrated the potential for heat recovery. Here, ISMs showed a greater potential for CO_2 reduction than traditional IS networks. (Yu, Li, Shi, & Qian, 2015)

Kwon et al. evaluated the environmental impacts of replacing aluminum components with magnesium in South Korean automobile production. Replacing Aluminum components with Using magnesium components can reduce fuel consumption by reducing the weight of the vehicle, however, producing magnesium requires the Pidgeon process in which a high level of carbon is released, thus offsetting the CO_2 reduction in the use stage of the product. IS approaches can be used to improve the Pidgeon process:

1. Using waste slag as a raw material for the cement industry.
2. Using urban waste energy as an energy for the Pidgeon process

The second strategy resulted in a 31% reduction in CO_2 emissions, much larger than the 5% reduction achieved with the first strategy. (Kwon, Woo, & Lim, 2015)

Extensive literature was developed on NISP that lead us to believe that facilitated networks hold significant potential to reduce waste, virgin resource use, and CO_2 emissions. A key component of these successes appears to be the ability of facilitated networks to encourage continued growth within IS networks. Paquin and Howard-Grenville evaluated the effect of facilitation on increasing the number of firms and number of projects in the network (2009). This research considers a number of firms and projects from 2005 to 2007. Over this period, the number of participating firms increased twofold and the number of projects that initiated also roughly doubled (Paquin & Howard-Grenville, 2009).

Paquin explored the idea of how serendipitous and goal-directed networks influence each other in industrial symbiosis (2012). A serendipitous process happens suddenly during chance meetings. A goal-directed process occurs through planning an organization and selecting a course of actions based on their collective activities. This paper contrasts three theories for IS development stages. Baas and Boons (2004) posit that different development occurs in three phases, Regional efficiency, Regional learning and Sustainable industrial district. Chertow and Ehrenfeld (2012) believe that the stages are Regional efficiency, Regional learning, and Sprouting and uncovering stages. Dom´enech and Davies (2010) also assert that Emergence, Probation and Development and expansion are the development levels for IS.

The similarity between all of the theories is the fact that "IS" will be matured by spreading trust and sharing norms. In the literature, these stages are known as "embeddedness". The author concludes that serendipitous actions play a more important role than Goal-directed actions in facilitated IS networks. Moreover, Paquin mentions that embeddedness is important both culturally and structurally in the way that it promotes trust and information-sharing between firms or connects them directly. (Paquin & Howard-Grenville, 2012)

In 2014 Paquin et al. used regression analysis to explore firm initiation and completion within IS networks. Using probit models, they demonstrated that firm's awareness, diversity among firms and sharing norms and trust increased the likelihood of project initiation and material exchanges between firms within the same industry. They established that having larger waste streams increases the likelihood of project completion; however, the greater potential value decreases it (Paquin, Tilleman, & Howard-Grenville, 2014).

In another study, Paquin et al. identified strategies and policies to improve environmental and economic values under regulatory constraints. They used a probit model to demonstrate the effects of IS on Eco-efficiency, which suggests generating more products by using fewer resources, and eco-development, which is the development of people from economic, social and political perspectives. Eco-efficiency and eco-development outcomes are analyzed under the situation of environmental regulation and economic constraints and exhibited that Eco-efficiency outcome is by increasing the landfill tonnage CO_2 reduction and cost-saving increased either. From eco-development perspective, they demonstrated that CO_2 reduction, business development, and employment number enlarged as well. (Paquin, Busch, & Tilleman, 2015).

So far, we've examined IS networks that emerged through self-organization and top-down planning. Now, we know about Paquin, Kwon, Hashimoto and other researchers that they identified relationships and mechanism about some important factors to establish IS network and promote firms to engage more in the IS network over time. Given the enormous potential of IS to reduce waste and resource use, it is critical to creating policy and regulatory structures to help establish IS networks, encourage firms to engage in these networks and continue to find new avenues for resource exchanges. The NISP dataset is rich and has allowed us to understand a number of important processes within IS. The obscure point in industrial symbiosis is how interfirm networks grow over time. Facilitated "IS" is suggested as a third way between the two mentioned ways of self-organization and third-party planning. (Paquin & Howard-Grenville, 2012) The National Industrial Symbiosis Program (NISP) developed in the UK in 2003 is an example of facilitated IS. The program started working in three regions, West Midlands, Scotland and Yorkshire & Humber with the support of regional agencies. NISP has influenced landfill diversion, carbon emissions and industry's reliance on virgin resources and had inspired similar programs in other regions such as North East, North West, East of England, London, South West, South East, Wales, Northern Ireland, East Midlands("NISP," n.d.). As the literature review shows, there are a limited number of successful IS and IE networks sites. These networks have generated important knowledge and insight on what makes IS networks successful. Most critically, data from existing IS networks indicate achievements such as decreasing landfill and carbon, improving industries, etc. however, the relatively small number of well-studied IS networks made developing robust policy based solely on real-world data. Modeling especially simulation models offer the opportunity to evaluate IS networks and potential policies under a wide range of situations to evaluate firm behavior and economic and environmental impacts.

Simulation methods have been used to evaluate and create policy in a wide variety of regulatory scenarios. For example, simulation methods were used to develop policies to regulate the nuclear energy industry, healthcare, biology, economy, telecommunications and other fields of science.

Models have been widely used in IE and IS contexts. These include OR models, social network analysis, LCA models, agent-based models, Input-output model and, System Dynamic. We are going to look at these models to see their pros and cons and decide about choosing the best fit model for our IS analysis.

4.1 Modeling approaches to IS and IE networks

To model an IS network it is vital to select a methodology which can include the key features of the network. In selecting a methodology to model an IS network we must first identify critical aspects of the network to ensure that they are adequately modeled. The key features in industrial symbiosis networks have been identified through reviews of similar models in the literature. The key characteristics that need to be modeled are population(El-sayed, Scarborough, Seemann, & Galea, 2012), dynamics of relationships between components (Batten, 2009), understanding the social etiology of complex conditions(El-sayed et al., 2012) , complexity(Sterman, 2001), evaluation of connectedness(Zhang, Zheng, Chen, & Yang, 2013), and considering each part of the system as an agent with different features(Bollinger, Davis, Nikolić, & Dijkema, 2012). The available data is also critical in choosing a model. In addition, since IS networks only occur when two firms have a match between wastes and their needs, we believe that the capability of the model to consider pairs is a key factor that needs to be considered to model an IS network.

Industrial Ecology and Industrial Symbiosis networks have been studied using a range of methods from engineering as well as social science. Engineering methods that have been used are an optimization, social network analysis, input-output analysis, systems models and agent-based models. We also review the relationship between IE and life-cycle assessment (LCA) models.

Agent-Based modeling:

Firms can enjoy financial and environmental benefits by working together. In IS and IE, we call this a synergy. Thus if they establish synergy in a larger network they can enjoy even greater benefits. Industrial Symbiosis is a complex system. From the simulation science perspective, it is a multipart network including dynamic relations, flows, and changing states. IS requires a powerful method both to understand and model the system. Batten attempts to demonstrate how “agent-based simulation and participatory modeling” can contribute to having a network where individuals can collaborate to achieve a better output (2009). Agent-Based Modeling (ABM) is a tool that comes to mind every time we have a system which has humans or human intelligence. In ABM we refer to decision makers as agents. ABM reflects individual variation in behavior and decision making. Regulation can be considered in ABM such as profit limitation, taxation, carbon credits, etc. Batten asserts that one of the barriers in IS networks is that the agents do not trust each other to collaborate giving or taking wastes to other agents. This problem can be solved in different iterations of the “companion agent-based simulation”. In companion ABM, there are three stages; evaluating the environment and the explicit influences on the agents, making the model based on the information gathered in the previous stage, doing the simulation to reach a better understanding from the current system; and finding new aspects of the system to concentrate on and evaluate. The model can combine different kinds of investors and simulate the environment in the way that they can both create trust and improve the system to learn from the system and make a decision. ABM models can give an alternative option for the future of a system and make several "what-if" states. Two major problems with ABM are considering a function that can be adapted to a variety of behaviors during the simulation. The other problem related to the stakeholders, which the ABM can also consider them as agents, that is convincing them to have consented to validate the model qualitatively (Batten, 2009). In an IS network, agents are impacted by interior and exterior forces. An ABM approach allows agents to adapt to these changes (Romero & Ruiz, 2014).

System Dynamic

System Dynamic Models, or systems models, consider interactions of various components in a system. It is a tool to help us understand a complex system and find the reason why some policies do not work properly or evaluate a new policy. System Dynamics include technical features of a network such as considering nonlinearity of the behaviors which can happen in human behavior and a society. An important issue in any modeling especially System dynamics is ensuring the model output to be close to the real world. Sterman explores the incompatibilities between the real system complexity and the capability of the tools to consider those complexities. Sterman also aims to find the system dynamic capability to understand the complications which can come from even simple models which have a few numbers of agents (2001). In a real system, events can be caused by several factors not just only one factor. We should consider that in a system our current decisions always influence the future status of the system thus this should happen in a model which want to simulate something in the real world. Another feature of the systems in the real world is the “time delay” of the consequence of an event and when a decision is made there would be a delay to see the effect of it (2001). The third feature of a system is “Flows and Stocks” which are not considered in most of the model which the events are not happening according to the theoretical movement that we expect (2001). Sometimes a challenging situation in a system could cause a good manager to make a poor decision. System Dynamics says that by correcting the system there would be a good decision out of the model. All of these features in system dynamics are in the form of positive or negative loops; the positive loops are those that are inspiration behaviors which can pace the process of a system; on the other hand, the negative loops are those that are limiting the process and they cause stability in the system (2001). The positive loops are getting the contagious events from the society and they soon adjust to them and have progress however negative loops as a “self-correcting” comes to make a balance in the system; thus, the system can include lots of positive and negative loops (Sterman, 2001).

The same issue for the model validation exists for the ABM. Romero et al. compare model reliability between ABM and SD in a constructed Dataset in different potential pair companies (2014). They describe ABM as a bottom-up model which looks at a system based on its people or agents while SD model has a general look at the system and try to make a balance in it by considering the process failure and risk evaluation in the system (2014). SD models cannot show the relation between the objects as well as the mission of them; in contrast, ABM can have the behavior of the agents and also it makes it possible to consider the effect of the nearby elements and both outer and inner features into the model (2014). Romero et al. based on these comparisons decide to choose ABM for their methodology since considering diversity between companies characteristics of the assets or actions play a vital role to make them collaborate together and ABM has the capability of considering these features (Romero & Ruiz, 2014).

Comparison between ABM and system dynamic makes us conclude that methodologies like "system dynamics" and "dynamic substance flow analysis" for considering industrial ecology are limited in including the influence of agents and material for endless entities. ABM is a good tool to beat the limitations of static and equation-based model styles. Bollinger et al. attempt to express the pros for ABM in industrial ecology in the metal sector. Their research question is as follows: "What conditions foster the development of a closed-loop flow network for metals in mobile phones?" There are three features in cellphone flow such as including rare metals, usage of cell phones which is rising and, minor parts of it are recycling in the world. Bollinger et al. believe while system dynamic considers procedures within the network, ABM considered agents all of whom are contributing to the life cycle of cell phones. (2012)In their ABM model, there are several agents which have decision-making regulations as well as properties such as their stock capacity, etc. all the agents go to the simulation model and decide whether they buy a metal, cellphone etc. The agents also have limited information about their surroundings; for example, a consumer does not know about the lifetime of the phone that he/she is buying. Bollinger et al. also considered different agents for each cell phone in their simulation model which are generating during the simulation and their metals are added to the network. All of the agents excluding the consumers are looking for maximizing their revenue (2012). After the simulation and comparison between ABM and equation-based simulation, they come up with the conclusion that ABM has many pros over the equation-based simulation such as considering merchandises as an agent which has its own characteristics, allow the actors to be different agents which can make an atmosphere to have different relations in the network and, let the agents be rational and make rational decision since they are really close to the real world (2012). Another advantage of ABM is that the flexibility of the model to make different metal flow arrangements during the simulation while in equation-based simulations the flows stay consistent during the simulation (Bollinger et al., 2012).

Optimization:

Optimization is mostly used for mathematical models in Operations Research (OR) that includes an objective function followed by constraint functions. IS has complex characteristic and behavior in its network; thus, when Optimization model includes the features, they make the model too complex which is difficult or sometimes impossible to solve. Kuznetsova et al. believe latest optimization methodologies in IS network have some problems such as considering global EIP optimum instead of local individual actors optimum, few optimizations objectives include both economic and environmental aspect; and finally, most of the uncertainty including systems weaknesses like individual object shutdown are not considered in the models. Kuznetsova et al. considered individual behaviors to make dynamicity which causes the model to meet both local and universal scenarios. One of the advantages of the model is considering the local optimum instead of the global optimum (2016). Until then most of the models just considered the global optimal option except a few models which had leader-slave optimization approach that technical barriers of the individual are just considered in these models and the actors did not consider as a smart agent (2016). The next advantages are that because of the mathematical complexity, the facets other than environment and economic did not consider before and the last advantages are that the insecurity in working did not consider in EIP models in the previous researches (2016). Kuznetsova et al. used the abstract model to solve the problem of complexity and also considering insecurity in the model. For the sake of considering each individual as an intelligent actor, they minimize total saving and working cost or the impact of industry on the environment; thus, the goals are reaching either EIP or the company objectives (2016). Kuznetsova et al. also considered

Environmental and Operational Conditions (EOC) to model Eco-Industrial Park (EIP) which respond to the second limitation which is lack of considering both economic and environmental aspects. For the last limitation, uncertainty not included in previous models, they add some technological constraints and some expectation for the individuals which can consider uncertainty in the real world (Kuznetsova, Zio, & Farel, 2016).

For doing further research in this methodology, we looked at another research in OR models. One of the features of EIP models is being nonlinear because of having a various connection between actors and sharing various resources. Pan ET all, made different optimization models to solve problems in EIP network and also have an optimal answer to their model. Considered this model, they were also able to find the optimum for the distance and amount of waste or by-product exchange to reduce the raw material convergence (2016). Pan et al, think that in EIP optimization it is so important to look at the different networks in their current position. Before this research, all of the papers just focused on the material or energy exchanges because considering all resources in a network makes a trouble in computation (2016). The mathematical model is advanced enough to predict the individual performance; they propose a multi-level modeling to do the optimization of EIP networks and levels of individual actions, processes, firms and industrial networks are considered in the model consequently (2016). EIP models are so complex if it includes all the system features and for solving Mathematical complexity which is nonlinearity some approaches is needed to simplify the computation and reach the optimal solution. Pan et al, propose several of optimization solution for solving the mathematical complexity such as using Taylor series expansions, heuristic rules, and variable initialization all of which make the function linear and they could solve it by Cplex software. The model target is to minimize the total network cost and the CO_2 emission (2016). They considered different scenarios for 1, 10, 20, 50 and, 100 years and for network cost, the optimal solution goes to the 100 years running of the model and also CO_2 reduction would be more in this scenario(Pan et al., 2016).

OR model can also consider population and dynamic of the relationship between object but it cannot include the pair feature of IS model which is too important and because sometimes IS model is non-linear it will make the optimization model too hard to solve.

Social network Analysis:

The other methodology which has been used to analyze IE and IS networks is Social network Analysis. In social network analysis, you can analyze the degree of connectedness which can show the potential connections in a network. Zheng et al. to model an IS network concentrated on the relationship between objects instead of objects itself. They considered different EIP such as Kalundborg, Choctaw, Kitakyushu, Styria, Guigang, etc. and examined the level of connectedness in each industrial park (2013). Based on table 1, they demonstrated that degree of connectedness is low in all EIP networks(Zhang et al., 2013).

Table 1: Different IS network degree of connectedness (Zhang, Zheng, Chen, & Yang, 2013)

eco-industrial parks

Name of park	*D*	Number of paths
Xinjiang Shihezi	0.300	9
Guangxi Guigang	0.267	23
Shandong Lubei	0.152	20
Choctaw	0.145	13
Kalundborg	0.118	13
Shanghai Wujing	0.109	12
Kitakyushu	0.055	23
Tianjin TEDA	0.036	43
Styria	0.031	43
Changsha Huangxing	0.018	41

To have a better perception we looked at another research project of Social network Analysis in 2012. By improving the field of epidemiology in the research fields there were some restrictions on the existed tools. e.g the lingua franca model is limited first in population dynamic which the health population depends on several factors such as social unity, social values, and social care and also this model is not precise about this population (2012). Second, nonlinear characteristic of population dynamic which is the risk of being sick does not always follow the variation of exposure; in other words, sickness can control exposure, as well as exposure, can control the disease (2012). Third, some of the individuals' attribute such as race, gender, etc. are considered as exposure in the model (2012). El- Sayed1 et al. assert that for the social epidemiology subject there is a few research to explore the field. They attempted to collect the existed literature for the different models' applications in healthcare and in this regard, they compare two different methodologies in the epidemiology field based on exited literature (2012). First, they look at social network analysis model which the purpose is to recognize the flow between individuals of a network (2012). There are three important parts of the network which are a visualization of the network, finding features of the network and making a stochastic atmosphere in the network (2012). In the first part, this model makes a clear visual form from the reality of the network, it considers the characteristics of the network properly in which it can find the features such as the individuals' connections, their distance and, their degree of connectedness (2012). This modeling can also model a stochastic network; however, there are some limitations associated with this model such as first, you cannot generalize the results of the model from one network to other similar networks; the second limitation in the social network analysis is sometimes its results for objects connections is confusing to conclude that it is because of the internal tendency of objects or as a result of the environment and strategies in the network (2012). El- Sayed1 et al. also look at Agent-Based Model (ABM) which they believe that it is good at making individuals of a network and the concept of it in different levels and with all details; it can model all small and large behaviors in the network. When there are complex agents in a network, different environments that can affect agents' behavior and, complex connections between agents, ABM models are going to be the best fit to model the network (2012). This model able to update easily with the new policy or a new characteristic of an agent because this model focuses on the individual characters, and behaviors to make population rather than focusing, on the whole, gathered data from a population; thus, it is an appropriate model for social, political or, economic networks (2012). This model lets us measure different characteristics of a population, its social contacts and, the environment; it also lets us find the effect of relations, reaction, and interchange of contacts and outcomes of the network in a complicated network atmosphere (2012). In ABM model, researchers can evaluate the influence of counterfactuals on the outcome of the network and they could include the individuals'' features such as race or gender or the happening the society like exposures and it can be updated by the new relations or exposures which are similar to the real world (2012). El- Sayed1 et al. state that ABM model has an important feature which can test different policies and evaluate the network outcomes, this feature is a limitation for some models such as regression models which are overcome in ABM model (2012). There are also limitations associated with this model; first, because this is a stochastic model and every small thing in the lower levels could change so sometimes it is hard to understand the changes in what part and in which level affect the outcome; the second limitation is that because the output of ABM models is quantitative and in some subject such as predicting exact specification of health population may perceive and analyze in a prejudiced way; the third limitation is the validation of the model either by using real data to make the parameters or by backward work to make the conceptual model and compare the result with the real world is complicated (El-sayed et al., 2012). The last limitation is not related to our case since we have the data for a real network (NISP).

Input-output model

An input-output model is a model to make an equilibrium to the demand between different industries by calculating direct and indirect use of material based on the final demand. In the literature, there is also the use of I-O model in industrial symbiosis. Yazan et al. consider energy, substantial screams and, firm matches which needs the input from the IS network. They attempt to make a tool for companies or the government to arrange policies to reach their goals in IS network (2016). Yazan et al. applied the Enterprise Input-output model in IS network and they have a definition for a perfect IS network which is the time when the network demands are meet by the wastes or by-products produced within the network and talk about two terms of "excess or scarcity of waste". The primary one refers to the time that a waste amount is more than the demand in the network and the latter one refers to the opposite situation so in both cases they have to send the extra waste to the firms outside of the network or buy wastes from outside in the second case (2016). By happening any of the mentioned cases the network should be upgraded to become a perfect IS network; if there is a third party that plays a role to take or give the waste to the network, either by balancing the waste products to the final demand or by increasing supply amount (2016). If perfect IS happens, there would be a reduced cost in transportation part for carrying the material from/to the third party (2016). One way for reducing the waste production in case of excess waste in the network is to improve the technology in the way that reduces the amount of output waste in the network (2016). For this problem, it could be another way to store the waste for the time it uses within the network; this way could be reasonable if the cost of stocking the waste is reasonable (2016). Yazan et al. believe for the scarce case which the demand of the network cannot meet with the available waste in the network, the supply company can increase the amount of its production but it may be impossible because of the production constraints. Finally, the paper concluded that transportation cost, wastes' values and mentally surrounded-ness of agents are all important for the connection and cooperation of agents (2016). Their model is good for the IS networks with the variety of the wastes' types and by using of this model the decision-makers can find the most strategic waste in the network (2016). Decision makers can also understand by using this model that if the cost of getting perfect IS is higher (even though the distance of it to the perfect IS is low) compare to get perfect IS for another waste type, which the distance to perfect IS is high, they can decide to choose a correct waste type for synergy (2016). Yazan et al. at the end suggest while their model is good for decision makers in mentioned aspects, it is hard to force the firms to stay in the network and do the synergy; in another word, the firms decide to stay in the network based on their income from the network. At the end of their research Yazan et al. recommend that the randomness of the agents' decision could be better consider in some models such as dynamic models or agent-based models(Yazan, Romano, & Albino, 2016).

Life Cycle Assessment (LCA):

Another methodology which is used for IE and IS in the literature is Life Cycle Assessment (LCA). LCA is a detailed method rooted in a deep understanding of product design, manufacturing, using and disposing of. LCA methods are widely used to quantify the cradle-to-grave environmental impacts of supplementary tool to quantify parameters to see if it works in an environmental aspect or not. Mattila et al. explore the problem in the methodologies all of which happens when researchers use Life Cycle Assessment (LCA) in IS field. They consider different categories in research studies such as "analysis", "improvement", and "expansion" of the systems, "design and circular economy" (2012). Three of these categories are using for evaluation the current system and two of them are using for the development of the system in the future (2012). Mattila et al.

suggest using a suitable modeling method of "static" or "dynamic" when LCA is present. In the analysis stage in LCA method, it withdraws quantitative values out of the systems in the way that they can compare the systems together; the numbers can be made out of the value of the services or the output of the system (2012). Input-output models consider the economic aspect of the system by considering a model mixing LCA and IO model both environmental and economic aspects will be considered which is called "IO-LCA" model (2012). The "improvement" stage is analogous to an undeveloped system; however, for expanding the system which is the next stage the study of a market is needed since we need to know what would happen in case of stopping in its current situation (2012). For designing a new network, it is important to have LCA in the very first steps because buying the facility for the network purposes should be considered in economic planning (2012). In the last stage to have a long-term look at the system, we should change the economic situation and use the "circular economy" which intends to have no use of raw material and reduce the environmental impact (2012). Finally, Mattila et al. result that LCA is a method to quantify the current system for environmental computations. Thus it helps to compare the current system to the ideal one and we can improve the system by applying new or better strategies; but still, it is a limited method to model an IS network (Mattila, Lehtoranta, Sokka, Melanen, & Nissinen, 2012). As shown in Table 2, there are benefits and dis-benefits with each methodology under consideration. However, Agent-based models are the best fit for describing IS network as well as structuring policy solutions to encourage IS; since, the firms include people's decisions and we considered them as intelligent agents thus, we choose Agent-Based simulation for modeling such a network. ABMS can incorporate most network features. Moreover, ABM is well suited to consider a variety of parameter values to better assess outcomes under unexpected uncertainties. By having changes during the time we can have other alternatives which cause our strategy to become more dependable and the environment to become more sustainable. Developing robust policy solutions requires understanding IS networks under a broader set of scenarios and conditions. Robust Decision Making(RDM) is such tools which have the feature of multiple views for the future that can help us and give us different alternatives which can be adopted in the future and help to have a sustainable environment (Lempert & Groves, 2010). Accordingly, it would be valuable to consider RDM to reduce uncertainty in future.

Finally, by using the large dataset of NISP program we are able to develop an agent-based Simulation model. The dataset provides information about landfill diversion, CO_2 emissions as well as other information such as cost saving, distance and, the age of waste. We are modeling the facilitated industrial symbiosis based on the real IS network data and we evaluate the influence of that on landfill diversion and carbon reduction.

Table 2: the features of each methodology

Evaluation of various methods to analyze industrial symbiosis								
	methodology	Population	dynamics of relationships between components	understand the social etiology of complex conditions	complexity	evaluation of connectedness	What Kind of data it needs	include the feature of being a pair
1	Social network Analysis						Real	
2	Agent-Based Modeling						Simulated and real	
3	Optimization						Simulated and real	
4	LCA							
5	Input-output						Real	
6	System Dynamic						Simulated and real	

4.2 Contribution

In this work, we analyze the significant factors for that can motivate firms both to start synergy in the network and continue their synergy by adding more wastes in the network. We also examine some policies that can establish progress within the network and all of this analysis are based on our large dataset of NISP network in the UK.

5 Methodology for Optimizing Industrial Symbiosis Outcome

This chapter provides the details of the proposed methodology for improving the industrial symbiosis potentials with an objective to minimize the environmental footprints left by candidate companies. In order to achieve our goals, we proposed the following five steps methodology.

a. Review of industry data for the current industrial symbiosis practices
b. Statistical analysis of the data for identifying the significant factors that impact organizations' willingness to engage in IS
c. Develop a hypothesis that has potentials to increase the willingness of industry partners to engage in IS
d. Design and develop an agent-based simulation to test the effectiveness of introduced hypothesis
e. Provide guidelines to help decision makers (mainly public policymakers and think-tank organizations) to design policies and standards to maximize the potentials of IS.

5.1 Industry Data

We have an industrial Data from a facilitated industrial symbiosis in the UK which names National Industrial Symbiosis Program (NISP). In this program whether 2 firms are started or continued synergy in the network is evaluated. The data for potential influential data is gathered. Moreover, they evaluated some of the environmental impacts that reduced by applying the network. The result of this program between the years 2003 to 2012 was the initiation of 684 projects in the network which causes tones of thousands landfill reduction as well as Carbon reduction.

5.2 Identify significant factors that impact companies to engage in Industrial Symbiosis

NISP data that we have access to suggest there are 12 different factors influencing companies' decision to engage in an IS program. However, there is no clear picture available to suggest whether all these factors are equally important to establish a successful IS program or not. As a result, we have decided to statistically analyze the NISP data with an objective to understand the significance of these factors on companies' decision for engaging in an IS program.

In the previous works to find influential parameters, a probit model is used. Generally, regression functions are appropriate to find significant parameters because they are able to consider different parameters at the same time. In our study, we used Logistic Regression to find significant parameters.

Table 3: Factors considered for IS decision making process

Variable	Definition	variable	Definition
Distance to NISP facilitator	Average of the distance of firms to NISP	**Employment creation**	Average of the number of employees increase in firms in a pair as a result of joining NISP network
Waste Quantity	Average of the waste quantity of firms	**Jobs Created**	Average of the type of jobs created in firms in a pair as a result of joining NISP network
Landfill Diversion	Average of the landfill diversion of firms in a pair as a result of joining NISP network	**Jobs Safe Guarded**	Average of the jobs saved in firms in a pair as a result of joining NISP network
CO_2	Average of the carbon reduction of firms in a pair as a result of joining NISP network	**Age of waste**	Average of the age of firms' wastes in a pair as a result of joining NISP network
Cost Savings	Average of the costs that are saved in firms in a pair as a result of joining NISP network	**Experience in IS**	Average of the times that firms in a pair had the experience in joining NISP network
Turnover	Average of the amount received in sales of firms in a pair as a result of joining NISP network	**Distance**	The distance between two firms in a pair

5.2.1 Logistic Regression

Researchers used logistic regression models to deal with dichotomous outputs. Dichotomous outputs refer to binary outcomes where 1 indicates the occurrence of an event and 0 otherwise. In the NISP data, we have access to summarizes the industrial symbiosis results as dichotomous data (if two corporations decide to consider IS, then the result is 1 (occurs), otherwise the result is 0. Hence the logistic regression models naturally fit to investigate NISP data for factorial analysis. Another characteristic of logistic regression is the capability of handling several independent factors in the analysis. Figure 2 illustrates a sample case for the logistic function. In Figure 2, the vertical axis represents the z value of equation 1 and the horizontal axis demonstrates the f (z) in the function where z is a factor belonging to factor set (Z) (Kleinbaum & Klein, n.d.). As the value of az goes infinity the function would approach 1 and as z goes toward negative infinity the f (z) tend to approach 0. Consequently, we can interpret the result of this function to make a conclusion if an event is observed or not.

$$f(z) = \frac{1}{1+e^{-z}} \qquad (1)$$

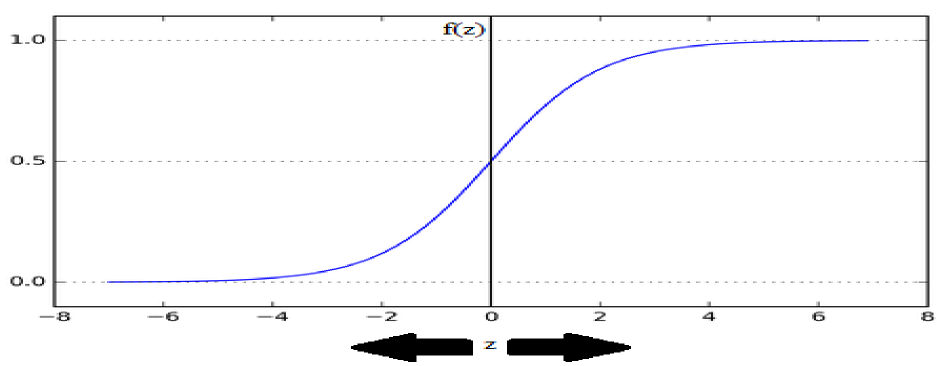


Figure 2: Showing the logistic function (Kleinbaum & Klein, n.d.)

In our case-study, a firm's initiation to start negotiations with a partner in the network to establish an IS is considered to be a significant achievement. Initiation in this context implies that a firm with different features joins the network to have synergy.

In the equation 2, a logistic regression, the probability of initiation is estimated as a function of logit. Thus in this function, the initiation is our dependent variable and all of our independent variables are considered in the logit function. This function gives us the probability of initiation for a given firm.

$$P(Initiation) = \frac{1}{1 + e^{-logit}} \qquad (2)$$

The logit function used in equation 2 is a regression model with multiple parameters (see equation 3).

$$logit = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \ldots \ldots \qquad (3)$$

Logistic regression also enables us to measure the interactions between continuous parameters. Therefore, the impact of interactions between different factors can be captured with a good precision. If the coefficient of a factor (β) is zero, two parameters have the same effect on the output. When β>0, it implies that the interaction of two parameters has a greater impact on the probability of initiation than the individual factor alone. In the case that β<0, it can be concluded that effect of interaction is less than the individual effect. In the following table (Table 4), interactions between different factors with the possibility of impacting on the probability of initiation is listed. The upper triangle in the table shows the same interaction as the lower triangle(Kleinbaum & Klein, n.d.).

While it is clear that the characteristics of logistic regression a good fit to analyze our industry data for the purpose of this research, the current literature suggests that an extra attention should be given to interpreting the results as they may easily mislead researchers. In real-life cases where the system is not fully contained from the effect of external factors, the outcome is the result of all influencing factors including controllable and uncontrollable even if they are not considered in the model. One of the vital problems resulted by ignoring those variables is the misinterpretation of Odds Ratios (OR) and Log-Odds Ratios (LnOR) (Mood, 2010).

Table 4: In this the potential combination of parameters are demonstrated. These combination will be tested to see if they can affect the outcome.

interactions between parameters				
	waste Quantity	Distance to NISP	Distance	landfill diversion
Waste Quantity		⁕	⁕	⁕
Distance to NISP	⁕		⁕	⁕
Distance	⁕	⁕		⁕
Landfill diversion	⁕	⁕	⁕	

While it is clear that the characteristics of logistic regression a good fit to analyze our industry data for the purpose of this research, the current literature suggests that an extra attention should be given to interpreting the results as they may easily mislead researchers. In real-life cases where the system is not fully contained from the effect of external factors, the outcome is the result of all influencing factors including controllable and uncontrollable even if they are not considered in the model. One of the vital problems resulted by ignoring those variables is the misinterpretation of Odds Ratios (OR) and Log-Odds Ratios (LnOR). (Mood, 2010)(Mood, 2010)

It is valuable to define the meaning of Odds-Ratio here since the interpretation of that would be helpful to understand cross-sectional studies like our research, and misperception of that would cause overestimation of the outcome. Odds is defined as the probability of happening an event divided by the probability of not occurring an event(Persoskie & Ferrer, 2010). However, odds for different samples would be equivalent if the risk of happening an event remains constant. In this case, we need the ratio between odds(Maucort-boulch, 2016).Let's suppose that we have a baseline risk of 40% for a disease, in this case, the number of vaccinated people who are infected is 20 and the number of them who are not infected is 80. In the group of not vaccinated people the number of infected people is 40 and the number of not infected people is 60. The odds for the first group is 0.25 (20/80) and for the second group is 0.33(40/60). The odds ratio will be 0.37 (0.25/0.33). If the risk decrease to 4% in vaccinated group 2 people will be infected and 98 would not be infected and in not vaccinated group 4 people will be infected and 96 people would not be infected. The odds of them are 0.02 and 0.042 respectively and the odds ratio will be 0.48. By decreasing the risk, it is more probable to have odd events which in this case is having less infected people.(Persoskie & Ferrer, 2010)

$$Odd = \frac{P}{1-P} \quad (4)$$

$$Odds\ Ratio = \frac{\frac{P_1}{1-P_1}}{\frac{P_2}{1-P_2}} \quad (5)$$

LnOR is the logarithm of the probability of occurrence of odd events divided by the estimated number of not occurring. In the logit regression, LnOR describes the rise of logit by growing of the specific independent variable while OR describe the rise of outcome responding to the growth of the independent variable.

LnOR and OR demonstrate the relationship between two independent variables. To make this point clearer, by adding one variable to the model and decreasing in LnOR and OR the relation between two variables will be determined. In this situation, the coefficient should also decrease otherwise the relation between variables and the outcome will be misinterpreted.

Mood (2010) suggests in her article strategies to avoid misinterpretation function outcome. One of the strategies which seem fit our model is standardizing the model. Mood suggested dividing all coefficients by the standard deviation. The standard deviation can be either sum of the standard deviation reached from all logit model for different samples or the fixed number of standard deviation which is 1.81($\sqrt{3.29}$).(Mood, 2010)

It does not seem reasonable to consider a fixed number as the standard deviation in the logit function so we choose the other way which is analyzing different sample sizes to get standard deviation out of each sample and divide all the logit coefficient by that.

Here in Table 5, you can see different samples in our population.

For the sake of finding standard deviation to make a standard logistic function we choose some samples from our population in the UK randomly. Thus the regions in Table 6 chose randomly and you can find some features of different chosen regions.

Table 5: list of different region in the UK

National Industrial Symbiosis Program(UK)-Regions			
North East	North West	West Midlands	East of England
Scotland	London	South West	South East
Wales	Northern Ireland	Yorkshire & Humber	East Midlands

Table 6: Chosen regions and some information about them

National Industrial Symbiosis Program(UK)-Regions					
Region	**Unmatched Firm Numbers**	**Matched Firm Numbers**	**number of Trials**	**the proportion of successes**	**Sample Size**
Wales	510	680	1190	0.5714286	1445602
London	893	708	1601	0.4422236	2597889
South East	967	748	1715	0.4361516	2989981
North East	678	469	1147	0.4088928	1360790
West Midlands	2464	1143	3607	0.3168838	15025801

We examined different significant parameters of different regions first and because there were many overlaps in their significant parameters and in general we did not find a significant difference between their result we merge all the data together to either increase the data points or get a more precise result.

Initiation:

Adapting to our dataset we need to find significant parameters and its coefficients so we run the logistic model to reach this goal. Using R-Studio makes us find the result for the sake of finding significant parameters. Table 7 is the input parameter in the logistic model.

As you can see in Table 7 “Distance to NISP”, “CO_2”, “Cost Savings”, “Age of waste” and, “Distance” are significant at the level of 0.05. The logit formula with our significant parameters are in function (6).

$$Initiation\ logit = b_0 + b_1(age\ of\ waste) + b_2(distance) + b_3(\text{distance to NISP}) + b_4(CO_2\ reduction) + b_5\,(\text{Cost Savings}) \qquad (6)$$

Table 7: Significant parameters results in the first running of logistic model for Initiation

Coefficients:	Estimate	P-Value
(Intercept)	-2.90E-01	0.00129 **
Distance to NISP	1.35E-03	0.05098 .
Waste Quantity	-3.02E-07	0.71
landfill Diversion	4.28E-06	0.39
CO_2	-5.86E-06	0.09664 .
Cost Savings	-1.11E-06	0.00250 **
Turnover	-6.07E-11	0.93
Employee	1.40E-05	0.93
Jobs Created	-4.57E-02	0.25
Jobs Safe Guarded	-1.77E-02	0.40
Age of waste	5.40E-05	2.31e-05 ***

experience	1.52E-01	0.53
Distance	2.47E-03	0.01959 *
Distance to NISP-Waste Quantity	1.36E-10	0.98
Distance -Waste Quantity	9.29E-09	0.45
Waste Quantity -landfill Diversion	4.65E-12	0.75
Distance to NISP-Distance	-1.47E-05	0.06540 .
landfill Diversion-Distance to NISP	8.28E-08	0.08508 .
landfill Diversion-Distance	5.21E-08	0.27
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Landfill diversion is an important parameter which we want to examine as an output from our model so we run the logistic regression one more time with the significant parameters and landfill diversion which gives us Table 8. In this new analysis landfill diversion in the level of 0.01 is significant. Thus the logit function change and it will be like function (7).

$$Initiation\ logit = b_0 + b_1(Landfill\ Diverted) + b_2(age\ of\ waste) + b_3(distance) + b_4(\text{distance to NISP}) + b_5\,(CO_2\ reduction) + b_6\,(\text{Cost Savings}) \qquad (7)$$

In Table 7 you can see that some of the multiplication of the parameters such as "distance to NISP*Landfill Diverted" and "distance to NISP*distance" are also significant is 0.05 level. And the updated expression for this part is the function number (8).

$$Initiation\ logit = b_0 + b_1(Landfill\ Diverted) + b_2(age\ of\ waste) + b_3(distance) + b_4(\text{distance to NISP}) + b_5\,(CO_2\ reduction) + b_6\,(\text{Cost Savings}) + b_7(\text{distance to NISP})(Landfill\ Diverted) + b_8(distance\ to\ NISP)(distance) \qquad (8)$$

After all for avoiding any misinterpretation, we standardize the coefficient by using formula (9) in function (8).

$$b'_{\mathrm{i}} = b_{\mathrm{i}} * \frac{\boldsymbol{s}_{\mathrm{x}}}{\boldsymbol{s}_{\mathrm{Y}}} \qquad (\mathbf{9})$$

All of the parameters coefficients will be multiply by their standard deviation and divided by the standard deviation of the dependent variable and we are going to get the formula (10).

$$
\begin{aligned}
Initiation\ logit = {} & b_0 + b_1(Landfill\ Diverted) * \frac{s_{x1}}{s_Y} + b_2(age\ of\ waste) * \frac{s_{x2}}{s_Y} + b_3(distance) * \frac{s_{x3}}{s_Y} \\
& + b_4(\text{distance to NISP}) * \frac{s_{x4}}{s_Y} + b_5\,(CO_2\ reduction) * \frac{s_{x5}}{s_Y} \\
& + b_6\,(\text{Cost Savings}) * \frac{s_{x6}}{s_Y} + b_7(\text{distance to NISP})(Landfill\ Diverted) * \frac{s_{x7}}{s_Y} \\
& + b_8(distance\ to\ NISP)(distance) \quad * \frac{s_{x8}}{s_Y} \quad (10)
\end{aligned}
$$

Table 8: Significant parameters for initiation

Coefficients:	Estimate	P-Value	Standard Deviation	Odds Ratio(OR)	LnOR
(Intercept)	-3.09E-01	0.000156 ***		0.7342081	-0.308962776
Distance to NISP	1.38E-03	0.043552 *	123.5899	1.0013772	0.001376253
landfill Diversion	8.70E-06	0.021840 *	48651.1300	1.0000087	8.69996E-06
CO_2	-5.73E-06	0.066337 .	47619.1700	0.9999943	-5.70002E-06
Cost Savings	-1.23E-06	0.000732 ***	244522.9000	0.9999988	-1.2E-06
Age of waste	5.38E-05	2.42e-05 ***	6282.9160	1.0000538	5.37986E-05
Distance	3.09E-03	0.001246 **	72.7559	1.0030955	0.003090719
Distance to NISP-landfill Diversion	7.91E-08	0.076870 .	6983242.0000	1.0000001	1E-07
Distance to NISP-Distance	-1.62E-05	0.035545 *	10418.4200	0.9999838	-1.62001E-05
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

In Table 8 you can see Odds Ratio and LnOR which I described the definition of that in the previous paragraphs. In the column of Odds Ratios, you can see the increase of dependent variable by increasing each parameter and keeping other parameters constant. Also in LnOR, you can see the increase of logit by increasing each parameter.

Completion:

The same procedure has been done for the completion part and Table 9 resulted from the first run of the logistic model.

As you can see different parameters at different levels are significant. The level that we considered is 5 percent. Because landfill diversion in this list is not significant, we run the model again with significant parameters and landfill diversion which gives us Table 10. All the parameters in the second run are significant in 0.05 level of significance. Thus, the logit function is function 11. Similar to the steps for initiation we standardize the logit function and we will reach function 12. Because the significant parameters in initiation and completion are the same so the logit function is also similar to different coefficients.

$$Completion\ logit = c_0 + c_1(Landfill\ Diverted) * \frac{s_{x1}}{s_Y} + c_2(Age\ of\ Waste) * \frac{s_{x2}}{s_Y} + c_3(Distance) * \frac{s_{x3}}{s_Y} + c_4\,(CO_2\ Reduction) * \frac{s_{x4}}{s_Y} + c_5\,(Cost\ Savings) * \frac{s_{x5}}{s_Y} \quad (11)$$

$$Completion\ logit = c_0 + c_1(Landfill\ Diverted) * \frac{s_{x1}}{s_Y} + c_2(age\ of\ waste) * \frac{s_{x2}}{s_Y} + c_3(distance) * \frac{s_{x3}}{s_Y} + c_4(CO_2\ reduction) * \frac{s_{x4}}{s_Y} + c_5\,(\text{Cost Savings}) * \frac{s_{x5}}{s_Y} \quad (12)$$

Odds ratio which shows the increase of the logit by increasing each parameter and LnOR which shows the increase of completion probability by increasing each parameter are shown in Table 10.

Table 9: Significant parameters for completion in the first running of logistic

Coefficients:	Estimate	P-Value
(Intercept)	-2.56E-01	0.01374 *
Distance to NISP	-7.99E-04	0.29743
Waste Quantity	3.68E-06	0.20525
landfill Diversion	3.91E-06	0.50389

CO_2	3.91E-06	0.28018
Cost Savings	9.73E-07	0.01055 *
Turnover	-1.69E-09	0.20048
Employee	3.19E-05	0.88607
Jobs Created	5.63E-02	0.54391
Jobs Safe Guarded	2.42E-02	0.26586
Age of waste	-5.39E-05	0.00131 **
experience	6.03E+01	0.94152
Distance	-3.13E-03	0.03011 *
Distance to NISP-Waste Quantity	-1.77E-08	0.40435
Distance -Waste Quantity	-1.37E-07	0.05133 .
Waste Quantity -landfill Diversion	-3.21E-12	0.73149
Distance to NISP-Distance	1.95E-05	0.03085 *
landfill Diversion-Distance to NISP	-8.49E-08	0.13357
landfill Diversion-Distance	-2.95E-08	0.77052
Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1		

Table 10: Significant parameters for completion

Coefficients:	Estimate	P-Value	Standard Deviation	Odds Ratio(OR)	LnOR
(Intercept)	0.225700000	0.00233 **		1.2540675	0.226392269
landfill Diversion	-0.000011270	0.00174 **	48651.13	0.9999883	-1.17001E-05
CO_2	0.000006260	0.04244 *	47619.17	1.0000063	6.29998E-06
Cost Savings	0.000001091	0.00484 **	244522.90	1.0000011	1.1E-06
Age of waste	-0.000053360	2.39e-05 ***	6282.92	0.9999463	-5.37014E-05
Distance	-0.001997000	0.03247 *	72.76	0.9980226	-0.001979358
Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

5.2.2 Simulation model

With an integrated understanding of the factors that influence a project's initiation and completion, we can now construct a simulation model. In the simulation model, each pair is considered an agent. Based on the four regions of Wales, London, South East, North East, West Midlands in the UK and the reality of the world we made the model. Different commodity types (called streams) are available in the regions. Each of the firms has a list of available wastes that consist of streams and sizes.

The simulation works in the following steps at each quarter:

1. **Recruitment**: new firms join the system and their resources are added to the pool of available Haves and Wants.
2. **Matching:** Haves and Wants of the same commodity are identified as a potential match. At this point, resources can be matched more than once.
3. **Initiation:** projects are selected, among the pool of potential matches, based on the facilitators' strategies and firms' intentions.
4. **Completion:** The pairs are evaluated based on their individual characteristics whether the initiated projects are likely to be completed.

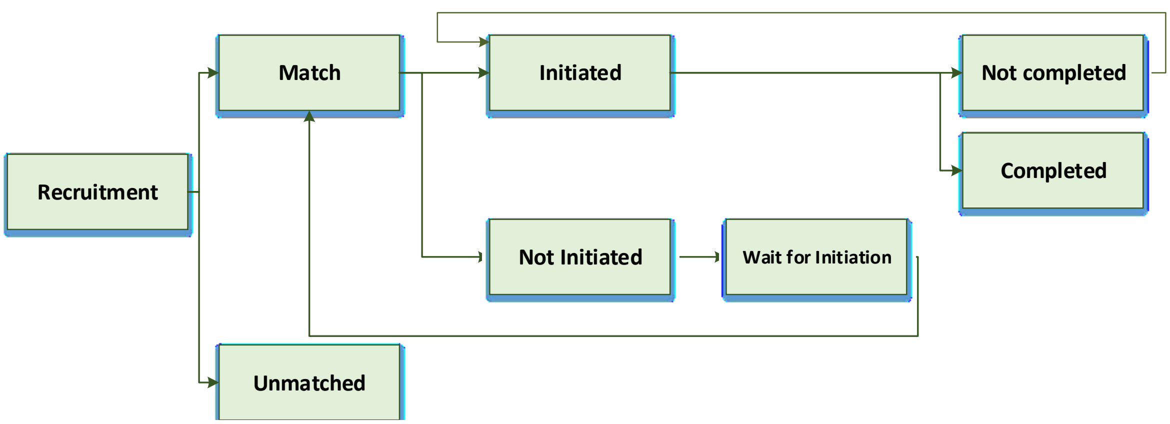


Figure 3: Simulation model

Recruitment

The model starts by generating a firm and randomly engages it active in the network activities. For the firms that are active, a random number as the amount of waste will be generated. According to the real data, 50 % of all the active firms are considered as "Have" firms, indicating that they have waste to bring to the network. The rest of the firms are considered "Want" firms and will make further use of the waste.

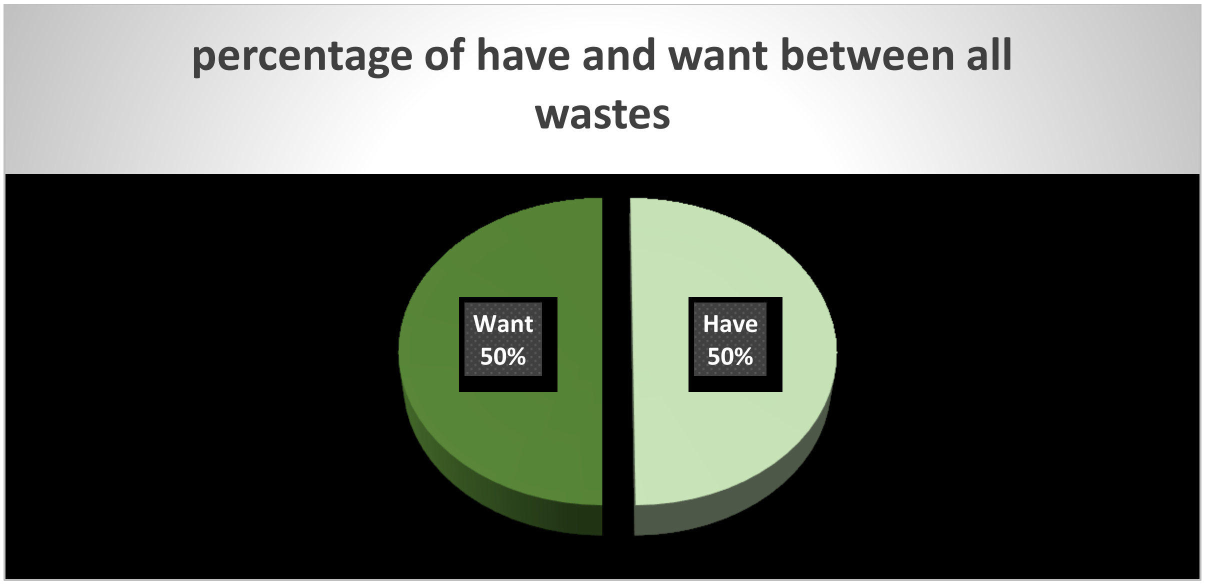


Figure 4: Have and Want percentage

Matching wastes

In order to match the firm's wastes, we analyzed the real data. Each stream then receives a percentage of the total number of firms. There are some firms that are not able to be matched with the other firms and they will be called the unmatched firms.

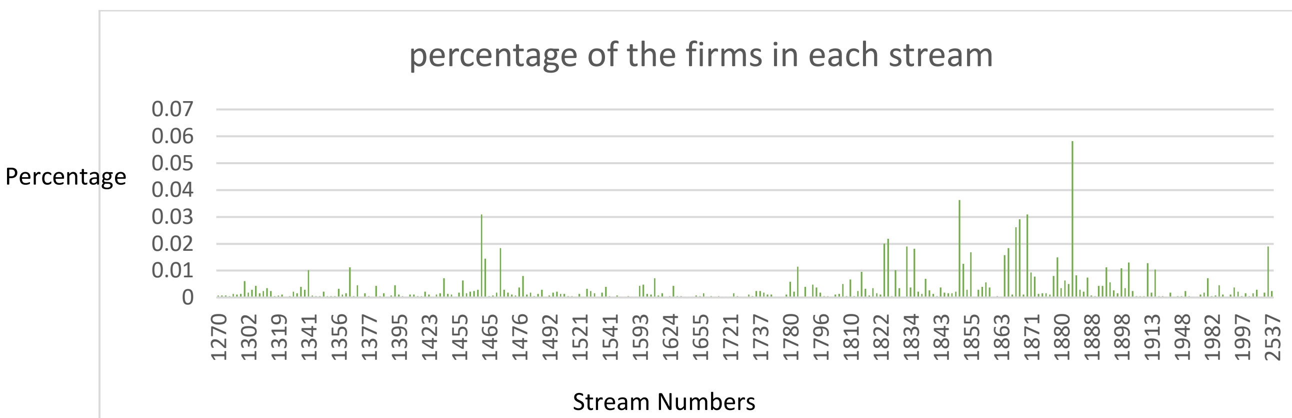


Figure 5: members' percentage

In each stream, there are different pairs formed by combinations of the firms in a specific stream. All different possible combinations will be considered in this step.

Initiation

From the pool of potential pairs, some projects will be selected for initiation. The selection process is according to some parameters like Distance to NISP, landfill Diversion, CO_2, Cost Savings, Age of waste and, Distance which are all generated by probability distributions.

The function to determine the set of projects to be initiated is predicted by function 13&14. In reality, this function is the product of both the selection strategy of the facilitators and the acceptance or rejection of projects by firms; although, the data available does not allow us to make a distinction between the two. To model the selection process, we adopted a selection model of the same form as a logistic regression model:

$$P(Initiation) = \frac{1}{1 + e^{-logit}} \qquad (13)$$

$$\begin{aligned} &Initiation\ logit \\ &= b_0 + b_1(Landfill\ Diverted) * \frac{\boldsymbol{s}_{\text{x1}}}{\boldsymbol{s}_{\text{Y}}} + b_2(age\ of\ waste) * \frac{\boldsymbol{s}_{\text{x2}}}{\boldsymbol{s}_{\text{Y}}} \\ &+ b_3(distance) * \frac{\boldsymbol{s}_{\text{x3}}}{\boldsymbol{s}_{\text{Y}}} + b_4(\text{distance to NISP}) * \frac{\boldsymbol{s}_{\text{x4}}}{\boldsymbol{s}_{\text{Y}}} + b_5\,(CO2\ reduction) * \frac{\boldsymbol{s}_{\text{x5}}}{\boldsymbol{s}_{\text{Y}}} \\ &+ b_6\,(\text{Cost Savings}) * \frac{\boldsymbol{s}_{\text{x6}}}{\boldsymbol{s}_{\text{Y}}} + b_7(\text{distance to NISP})(Landfill\ Diverted) * \frac{\boldsymbol{s}_{\text{x7}}}{\boldsymbol{s}_{\text{Y}}} \\ &+ b_8(distance\ to\ NISP)(distance) \quad * \frac{\boldsymbol{s}_{\text{x8}}}{\boldsymbol{s}_{\text{Y}}} \quad (14) \end{aligned}$$

This allows us to directly use the coefficients that were previously found in the initiation regression model. According to the parameters for each of the pairs, there is a probability for initiating in the network which is determined by the initiation formula.

Data Analyzing:

One of the important parts of the simulation is identifying the probability distributions that best represent the input parameters. The probability distributions enable us to generate an abundance of data so real-life cases can be simulated with high accuracy. Thus, considering appropriate distributions for the given data plays a critical role to have good simulation results. Accordingly, the collected data were analyzed to estimate the probability distributions as discussed below.

Distance: There are two types of distance: the distance between two firms in a potential pair; and distance from the NISP facilitator. In order to identify the probability distributions, Chi-Square and Kolmogorov tests were utilized

According to the Table 11 and 12, the p-values for both Chi-Square Test and Kolmogorov Test are less than 0.005 and 0.01, respectively, which is favorable in all cases. In order to further investigate the best fitting distribution, we also compared the Square Errors. The results show that Erlang and Exponential distributions are the most appropriate probability distributions for "Distance to NISP". Moreover, for the parameter "Distance" both Exponential and Gamma

Distribution were a good fit. In our experiments, we used the exponential distribution. Thus, for both distance parameters, exponential distribution is considered in our simulation model.

Table 11: Different distribution Distance to NISP

Distance to NISP							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.02				
Erlang	p-value < 0.005	p-value < 0.01	0.01				
Exponential	p-value < 0.005	p-value < 0.01	0.01				
Gamma	p-value < 0.005	p-value < 0.01	0.20				
Lognormal	p-value < 0.005	p-value < 0.01	0.34	0	4900	93.2	5.5
Normal	p-value < 0.005	p-value < 0.01	0.39				
Triangular	p-value < 0.005	p-value < 0.01	0.63				
Uniform	p-value < 0.005	p-value < 0.01	0.65				
Weibull	p-value < 0.005	p-value < 0.01	0.02				

Table 12: Different distribution Distance

Distance							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.01				
Erlang	p-value < 0.005	p-value < 0.01	0.01				
Exponential	p-value < 0.005	p-value < 0.01	0.01				
Gamma	p-value < 0.005	p-value < 0.01	0.00				
Lognormal	p-value < 0.005	p-value < 0.01	0.03	0	609	54.4	4.2
Normal	p-value < 0.005	p-value < 0.01	0.09				
Triangular	p-value < 0.005	p-value < 0.01	0.13				
Uniform	p-value < 0.005	p-value < 0.01	0.16				
Weibull	p-value < 0.005	p-value < 0.01	0.01				

Landfill Diversion: Another parameter is landfill diversion and we follow the same instruction for the distance parameters. Looking at the results of both Chi-Square Test and Kolmogorov Test shows the exponential distribution is a good fit distribution for Landfill Diversion as well. Thus, exponential distribution is considered in our simulation model.

Table 13: Different distribution landfill diversion

landfill diversion							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.06	0	3000000	17100	11.4
Erlang	p-value < 0.005	p-value < 0.01	0.00				
Exponential	p-value < 0.005	p-value < 0.01	0.00				
Gamma	p-value < 0.005	p-value < 0.01	0.42				
Lognormal	p-value < 0.005	p-value < 0.01	0.65				
Normal	p-value < 0.005	p-value < 0.01	0.41				
Triangular	p-value < 0.005	p-value < 0.01	0.85				
Uniform	p-value < 0.005	p-value < 0.01	0.87				
Weibull	p-value < 0.005	p-value < 0.01	0.00				

Carbon Reduction (CO_2): We also need a good fit distribution function to be considered to act in place of carbon reduction parameter in the simulation model. Chi-Square Test and Kolmogorov Test are used to find the good fit distribution. Consequently, exponential distribution is chosen to play the part for CO_2 in the simulation model.

Cost Saving: According to table 15, p-value for Chi-Square Test and Kolmogorov Test is promising for all distribution function. By doing the same procedure for the other parameters we choose an exponential distribution to represent input for cost saving to the simulation.

Table 14: Different distribution CO_2

CO_2							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.08	0	3000000	12200	11.4
Erlang	p-value < 0.005	p-value < 0.01	0.00				
Exponential	p-value < 0.005	p-value < 0.01	0.00				
Gamma	p-value < 0.005	p-value < 0.01	0.50				
Lognormal	p-value < 0.005	p-value < 0.01	0.74				
Normal	p-value < 0.005	p-value < 0.01	0.44				
Triangular	p-value < 0.005	p-value < 0.01	0.89				
Uniform	p-value < 0.005	p-value < 0.01	0.91				
Weibull	p-value < 0.005	p-value < 0.01	0.00				

Table 15: Different distribution Cost Saving

Cost Saving							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.08	0	9000000	85000	13.1
Erlang	p-value < 0.005	p-value < 0.01	0.00				
Exponential	p-value < 0.005	p-value < 0.01	0.00				
Gamma	p-value < 0.005	p-value < 0.01	0.54				
Lognormal	p-value < 0.005	p-value < 0.01	0.75				
Normal	p-value < 0.005	p-value < 0.01	0.60				
Triangular	p-value < 0.005	p-value < 0.01	0.85				
Uniform	p-value < 0.005	p-value < 0.01	0.87				
Weibull	p-value < 0.005	p-value < 0.01	0.00				

Age of waste: The same process has been done to for choosing the best fit distribution function to act in place of the age of waste. After doing the analysis, exponential distribution is chosen to play the part instead of Age of waste parameter.

Table 16: Different distribution age of waste

age of waste							
Distribution	**Chi Square Test**	**Kolmogorov Test**	**Square Error**	**Min Data**	**Max Data**	**Sample Mean**	**Sample Std Dev**
Beta	p-value < 0.005	p-value < 0.01	0.10608	0	78700	4120	9.4
Erlang	p-value < 0.005	p-value < 0.01	0.076674				
Exponential	p-value < 0.005	p-value < 0.01	0.076674				
Gamma	p-value < 0.005	p-value < 0.01	0.074171				
Lognormal	p-value < 0.005	p-value < 0.01	0.078667				
Normal	p-value < 0.005	p-value < 0.01	0.387907				
Triangular	p-value < 0.005	p-value < 0.01	0.43275				
Uniform	p-value < 0.005	p-value < 0.01	0.45778				
Weibull	p-value < 0.005	p-value < 0.01	0.074272				

Finally, the result of the distributions for all parameters are the following table:

Table 17: Different distribution for each parameter

Parameter	Distribution	Chi-Square Test	Kolmogorov Test	Square Error
Distance to NISP	Exponential(46.6)	p-value < 0.005	p-value < 0.01	0.01
landfill diversion	Exponential(8.57e+003)	p-value < 0.005	p-value < 0.01	0.00

CO_2	Exponential(6.1e+003)	p-value < 0.005	p-value < 0.01	0.00
Cost Saving	Exponential(4.25e+004)	p-value < 0.005	p-value < 0.01	0.00
age of waste	Exponential(2.06e+003)	p-value < 0.005	p-value < 0.01	0.08
Distance	Exponential(54.5)	p-value < 0.005	p-value < 0.01	0.01

Identification of the trend of initiation in the NISP data brings more accuracy to the model. The percentage of initiation in each year from 2006 to 2012 in figure 6 demonstrates that there is no special trend for initiation; thus, we apply steady state for the trend of initiation in our simulation.

Figure 6: Percentage of initiated firm in each year from 2006 to 2012

So far we have identified the list of significant parameters and the probability distribution to represent them in the simulation. Now, let us introducing our approach to incorporate the stochastic nature of the problem. As discussed earlier, the logistic regression function provides the probability of initiation based on the input parameters. From the dataset that we collected, even when the initiation probability is low, there are some successful initiations between organizations. In order to incorporate this reality into our simulation model, we categorized the initiation success rate according to the probability of initiation obtained from the regression model. Table 18 shows a discrete distribution table such that if $p^{-} \leq p < p^{+}$ (where p is the probability of initiation from the regression model and p^{-} and p^{+} are lower and upper limits) then the probability of initiation is estimated from the historical data set. Accordingly, when the simulation model generates a probability of initiation (p), using discrete distribution, we determine if the initiation actually happens.

Table 18: percentage of initiation

Percentile	percentage of initiation
0-0.05	0.00%
0.05-0.1	0.00%
0.1-0.15	0.00%
0.15-0.2	0.00%
0.2-0.25	0.00%
0.25-0.3	16.67%
0.3-0.35	22.00%
0.35-0.4	23.33%
0.4-0.45	47.54%
0.45-0.5	52.58%
0.5-0.55	75.00%
0.55-0.6	79.00%
0.6-0.65	83.33%
0.65-0.7	85.00%
0.7-0.75	84.62%
0.75-0.8	100.00%
0.8-0.85	100.00%
0.85-0.9	100.00%
0.9-0.95	100.00%
0.95-1	100.00%

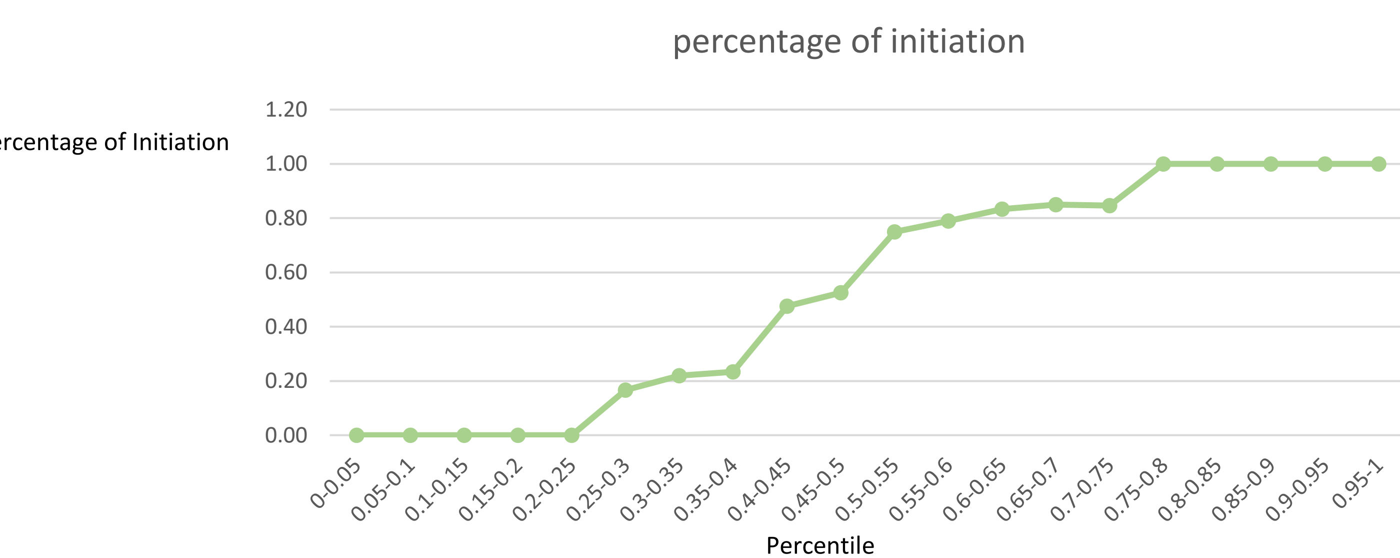


Figure 7: Percentage of initiation in each boundary of the initiation probability.

Completion

Accordingly, between the projects that initiate in the previous stage, some of them will complete their work in the network and continue establishing synergy or construct additional exchanges. The complete projects will be chosen based on the completion probability (Function 15 and 16) as well as the random number generated by a uniform distribution which will be described in the following paragraphs.

$$Completion = \frac{1}{1 + e^{-logit}} \qquad (15)$$

$$\begin{aligned} &Completion\ logit \\ &= c_0 + c_1(Landfill\ Diverted) * \frac{s_{x1}}{s_Y} + c_2(age\ of\ waste) * \frac{s_{x2}}{s_Y} + c_3(distance) * \frac{s_{x3}}{s_Y} \\ &+ c_4(CO_2\,reduction) * \frac{s_{x4}}{s_Y} + c_5\,(\text{Cost Savings}) * \frac{s_{x5}}{s_Y} \qquad (16) \end{aligned}$$

This interpretation lets us look at the trend of completion of the data. The trend of the completion percentage in figure 8 makes us get the steady state for completion as well.

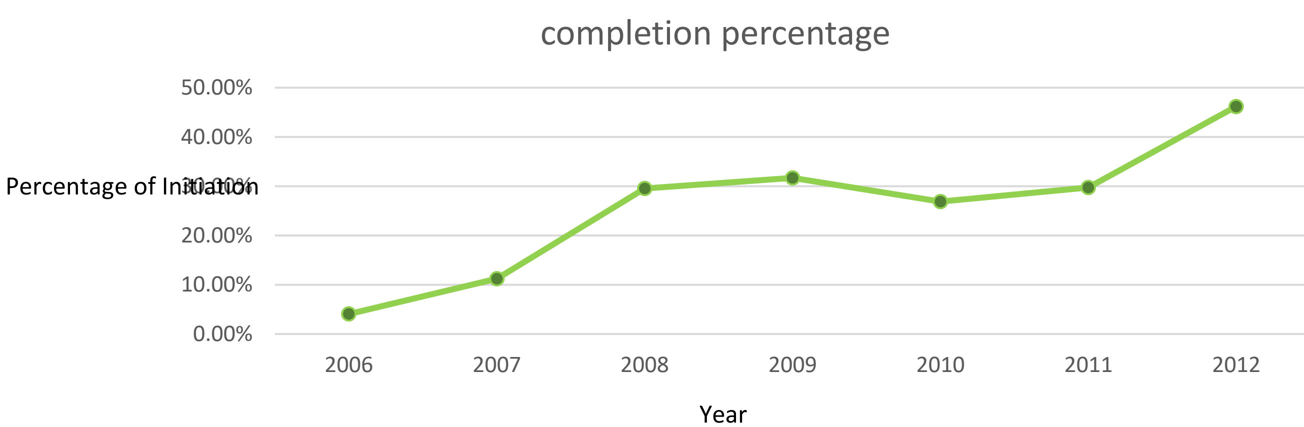


Figure 8: Percentage of completed firm in each year from 2006 to 2012

Consequently, to encompass the stochastic nature of the problem for completion part, we analyze the rate of successful completions in our dataset as well (Table19 and Fig9). Based on the probability of the completion, we categorized the completion success rate according to the probability of completion obtained from the regression model. Table 19 illustrates a discrete distribution table such that if $p^- \leq p < p^+$ (where p is the probability of completion from the regression model and p^- and p^+ are lower and upper limits) then the probability of completion is estimated from the historical data set. Consequently, when the simulation model generates a probability of completion (p), using discrete distribution, we determine whether the completion actually happens.

Table 19: percentage of completion

percentile	percentage of completion
0-0.05	0.00%
0.05-0.1	0.00%
0.1-0.15	0.00%
0.15-0.2	0.00%
0.2-0.25	0.00%
0.25-0.3	15.38%
0.3-0.35	16.00%
0.35-0.4	16.67%
0.4-0.45	38.46%
0.45-0.5	40.00%
0.5-0.55	47.42%
0.55-0.6	52.46%
0.6-0.65	76.67%
0.65-0.7	78.00%
0.7-0.75	83.33%
0.75-0.8	100.00%
0.8-0.85	100.00%
0.85-0.9	100.00%
0.9-0.95	100.00%
0.95-1	100.00%

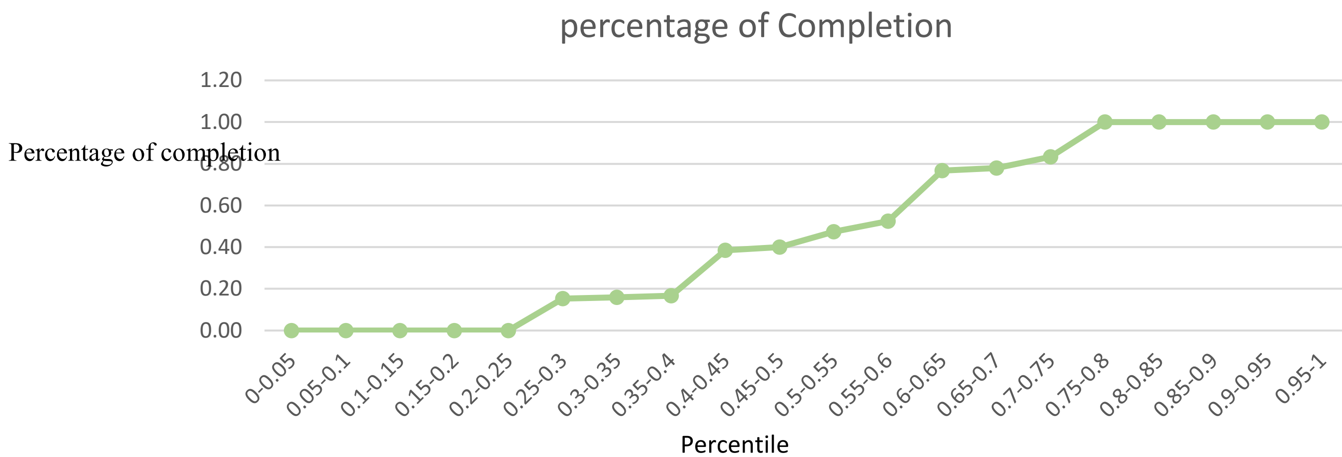


Figure 9: Percentage of completion in each boundary of the completion probability.

6 Results:

In this section, we present the numerical result. First, the simulation model is validated by comparing the success output of the 18 iterations with the success rate captured from the real network data. Section 4.1 provides the details of the validation. Next, we summarize the simulation result. Later, sensitivity analysis and trust analyses will be presented.

6.1 Validation of the simulation model:

Our sample data include information about 3748 firm projects from five regions in the UK. These projects have potential to form 1361 pairs which mean the combination of two firms that can start synergy in the network. Among these 1361 pairs, 677 pairs successfully established synergy. It means 49.74 % of eligible pairs have initiated industrial symbiosis. In the simulation model, we considered different combinations of firms in each stream. Based on the data, we can estimate the possible pairs given that a total number of firms in the network is known. For instance, if we have 1000 firms in the network, we could have 3378 pairs and there are many firms that cannot match to another firm. This means that in some cases one firm can be matched with more than one firm and there are streams that one firm could be matched with ten different firms while just one of them could initiate. Reminding the factors, each pair based on different parameters have an initiation probability out of logistic regression (function 13 and 14). After reaching the initiation probability we generate a random number by uniform distribution and based on table 18 we can see whether the pair will initiate or not. Many pairs as a result of having overlap to other pairs will be deleted from the network. Thus, the number of the potential success is different with the real success. For example, in the first iteration, you can see that we have 3378 pairs out of 1000 firms which 1756 of them could potentially initiate however just 308 of them had the chance of initiation because of the mentioned overlap. Since in the real data, different combinations did not consider we considered the potential success and we compared it to the success rate in real data which is 49.74%. In figure 10, you can see that in all cases (18 iteration) the success rate is too close to the reality.

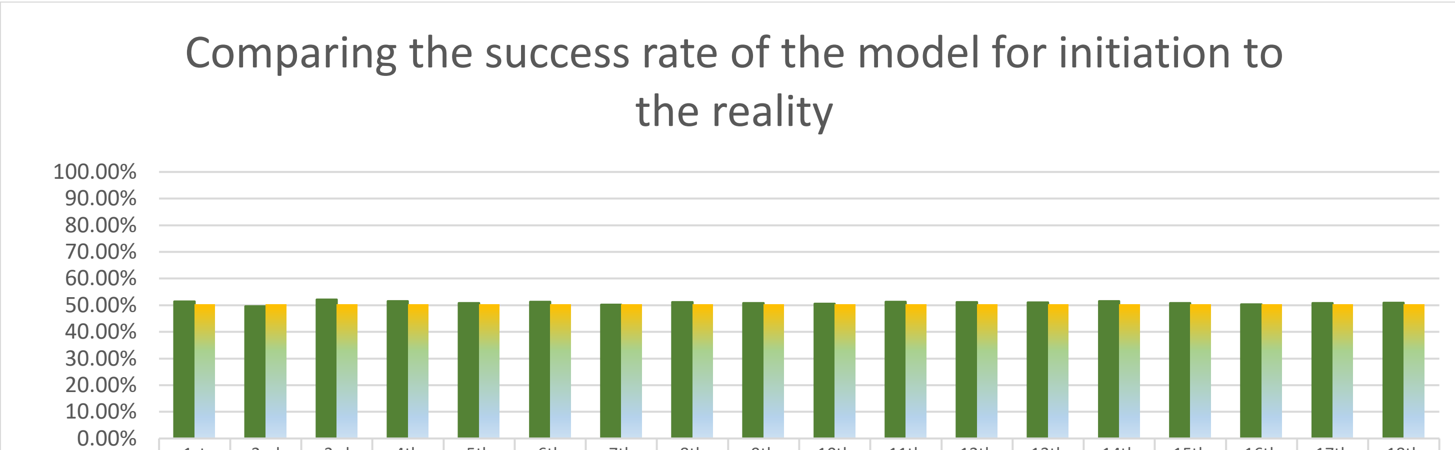
Table 20: Number of potential and real initiation in different iteration and different network sizes

iteration	Number of pairs	Potential success(initiation) in the model	Real Success(initiation) in the model	firm numbers
1st	3386	1739	299	1000
2nd	3355	1664	278	1000
3rd	3375	1760	299	1000
4th	3386	1746	295	1000
5th	3372	1712	294	1000
6th	3400	1744	291	1000
7th	7872	3957	483	1500
8th	7950	4069	507	1500
9th	7987	4063	503	1500
10th	7891	3992	499	1500
11th	7930	4064	496	1500
12th	7974	4079	502	1500
13th	14082	7196	693	2000
14th	14020	7222	689	2000
15th	13938	7089	686	2000
16th	14015	7054	698	2000
17th	14040	7143	698	2000
18th	13997	7123	689	2000

Table 21: Parentage of initiation in in 18 iteration with different network sizes

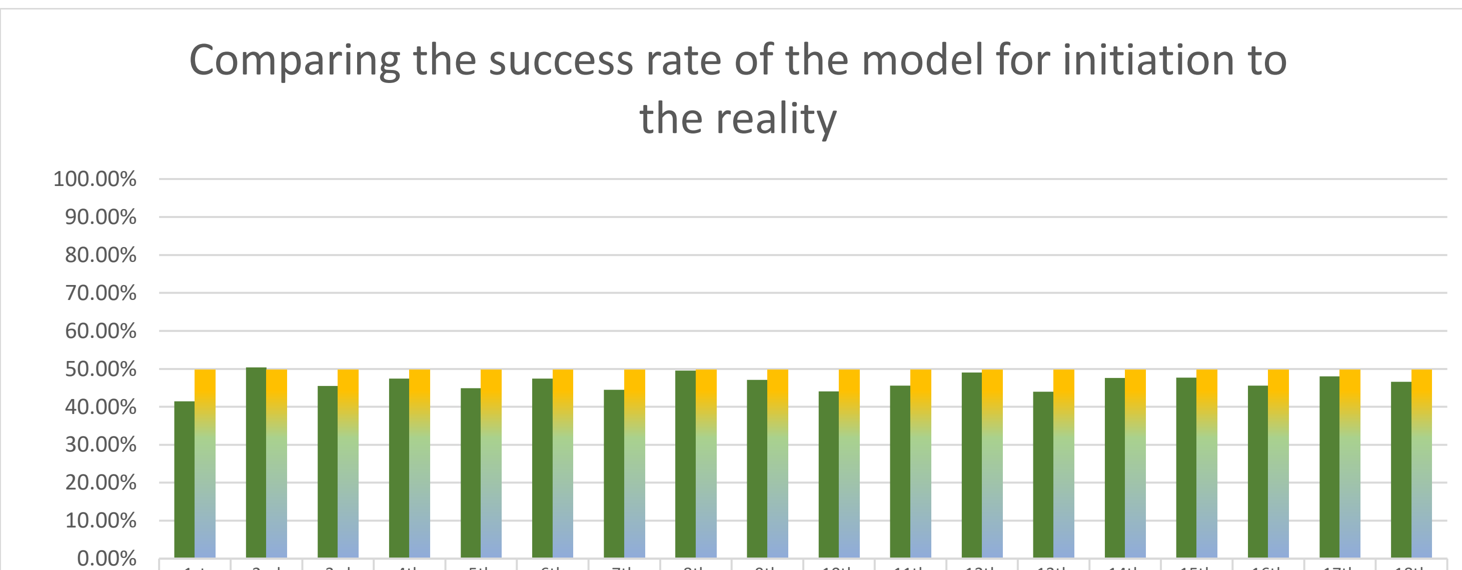
iteration	percentage	iteration	percentage
1st	51.36%	**10th**	50.59%
2nd	49.60%	**11th**	51.25%
3rd	52.15%	**12th**	51.15%
4th	51.57%	**13th**	51.10%
5th	50.77%	**14th**	51.51%
6th	51.29%	**15th**	50.86%

7th	50.27%	**16th**	50.33%
8th	51.18%	**17th**	50.88%
9th	50.87%	**18th**	50.89%



	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	17th	18th
Simulation	51.36%	49.60%	52.15%	51.57%	50.77%	51.29%	50.27%	51.18%	50.87%	50.59%	51.25%	51.15%	51.10%	51.51%	50.86%	50.33%	50.88%	50.89%
real case	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%	50.26%

Figure 10: Comparison of percentage of initiation in simulation model and the real data



	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	17th	18th
Simulation	41.47%	50.36%	45.48%	47.46%	44.90%	47.42%	44.51%	49.51%	47.12%	44.09%	45.56%	49.00%	44.01%	47.61%	47.67%	45.56%	47.99%	46.59%
real case	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%	49.74%

Figure 11: Comparison of percentage of completion in simulation model and the real data

In completion part, pairs are chosen from the pool of initiated pairs. So, we directly compare the model output with the completion rate in real data. In 18 iterations the success rate for completion in the simulation is close to the reality which is 50.26% and you can see that in figure 11 and Table 22.

Table 22: Parentage of completion in 18 iteration with different network sizes

iteration	simulation percentage	iteration	simulation percentage
1st	41.47%	**10th**	44.09%
2nd	50.36%	**11th**	45.56%
3rd	45.48%	**12th**	49.00%
4th	47.46%	**13th**	44.01%
5th	44.90%	**14th**	47.61%
6th	47.42%	**15th**	47.67%
7th	44.51%	**16th**	45.56%
8th	49.51%	**17th**	47.99%
9th	47.12%	**18th**	46.59%

6.2 Results of Simulation Model

In this section, we show the output of the model which is validated by comparing it to real data. The result in this section is count as the baseline scenario of the model.

Initiation Results:

The result of the simulation displays the effect of industrial symbiosis on landfill diversion and Carbon Reduction. If you look at the landfill diversion in figure 12, it shows the landfill diversion after synergy is established between different pairs, you can see that in most cases landfill diversion tonnage is increasing. It seems the more firms in the network, the more landfill diversion from the environment.

The same result happened for the carbon and you can see in figure 13 that increasing the number of firms in the network causes the network to have less carbon in the air.

However, people in the world are not totally expectable. Sometimes in the reality, two firms are totally matched and for initiation, everything works well but at the end, the manager for any reason decided not to start synergy with the other firm. Thus this situation considered in our simulation and that is why in some cases you see the variation in the amount of landfill diversion.

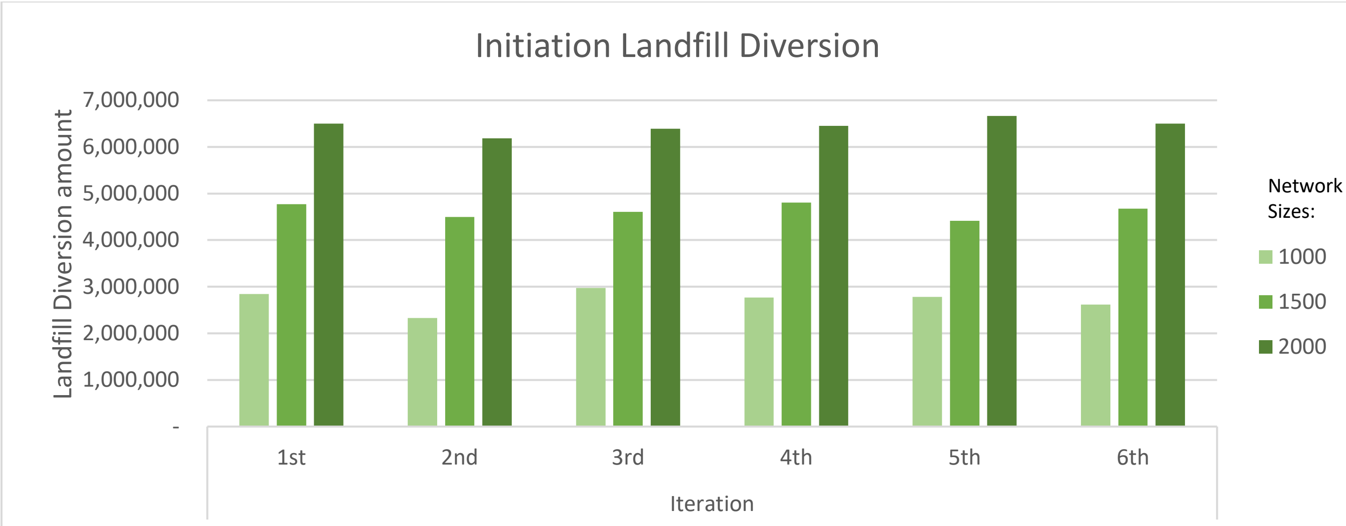


Figure 12: Landfill Diversion for initiation and different network sizes

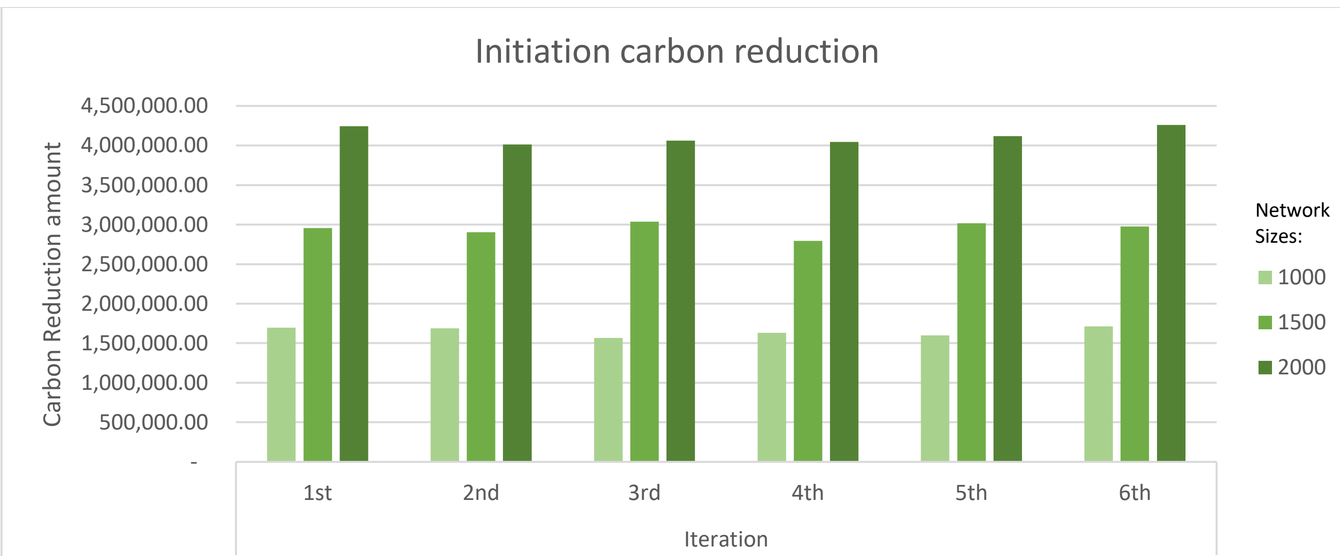


Figure 13: Carbon Reduction for initiation and different network sizes

Completion Results:

This approach is similar to the previous approach in initiation part. After pairs initiated in the network, some of them prefer to continue in the network either by continuing establishing synergy or creating additional exchanges over time. Therefore, you can see in figure 14&15 landfill diversion and carbon reduction amount increase in some cases and decrease in the others. Thus, we can consider some policies to motivate firms to come to the network and also complete it.

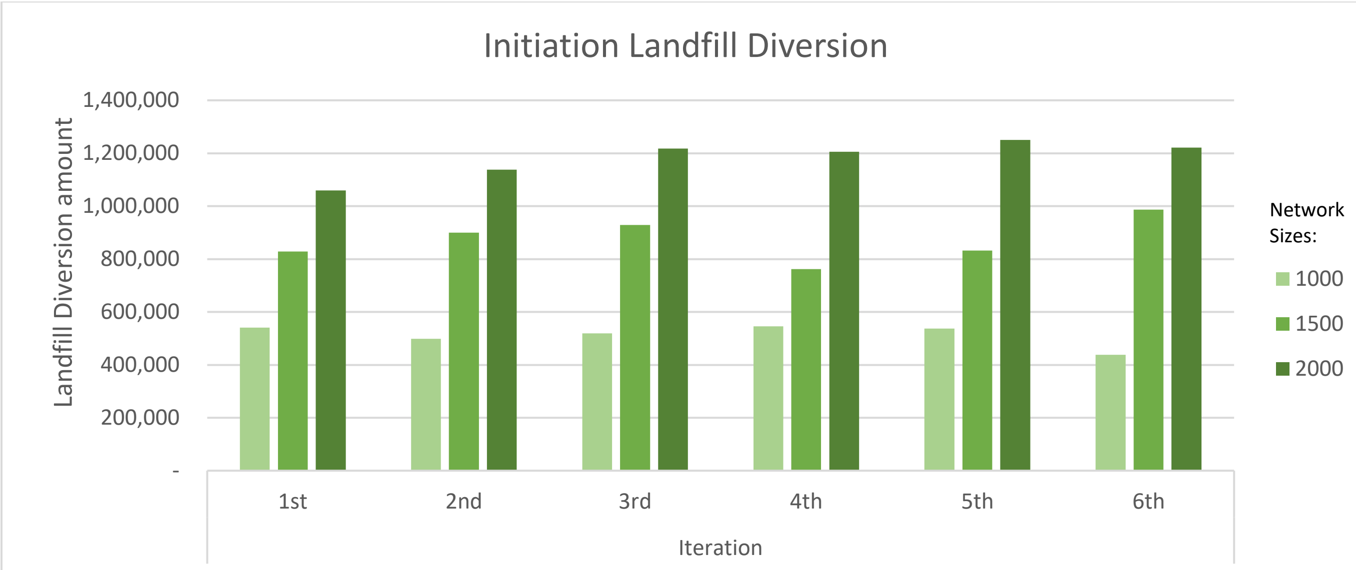


Figure 14: Landfill Diversion for completion and different network sizes

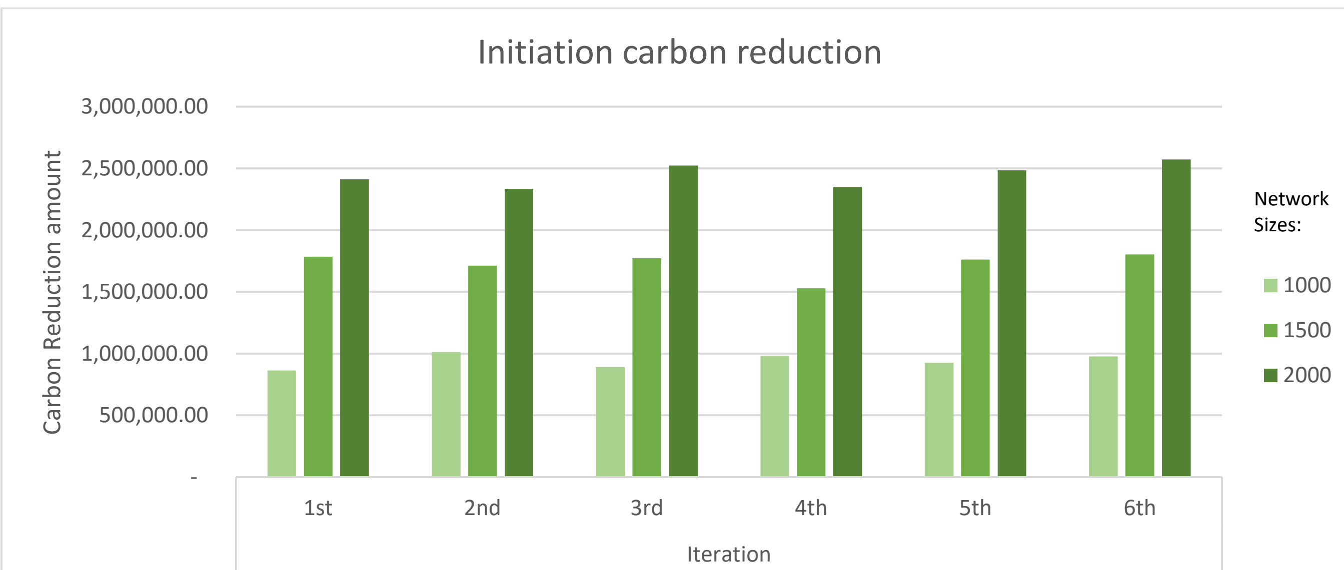


Figure 15: Carbon Reduction for completion and different network sizes

6.3 Sensitivity analysis:

In this part, we want to evaluate the results of the network by making changes in the parameters. There are six parameters and we are going to change some of them and see how the result would change.

Landfill diversion:

For doing a sensitivity analysis on landfill diversion we play with the landfill tax because it could be one of the factors that can affect manager decisions about coming to the IS network or continuing cooperation in it. Therefore, we considered this as an amount of money which if a pair reject to come to the network, they will lose that money and we subtract the benefit of the landfill diversion from the cost saving which is the money part of our function. The benefit of the landfill diversion computed by function (17) and it added to the objective function (function 18&19) and it is subtracted from the cost-saving variable (Cost Savings). The benefit of landfill diversion for a firm is the money that can save by paying less tax and it should be subtracted from the "Cost saving" variable. We increased the tax and looked at the effect of it on Initiation percentage, Completion percentage, Landfill diversion and, carbon reduction.

$$landfill\ diversion\ benefit = Landfill\ Tonage * Landfill\ Tax \qquad (17)$$

By looking at the initiation percentage (Figure 16) you can see that the percentage of initiation increased but it seems almost unchanged. According to European Union (EU) study result, there are different reasons that taxation as a single action does not have positive effects on waste managing (2001). They believe that tax should be just one part of the governmental regulation package for having a less environmental impact (2001). By increasing tax, companies would use other ways to escape from paying high taxes (2001). EU asserts that increasing the tax shows an increase in municipal wastes and also increase in corruptions for taking advantages of exemption ((Taxes & Report, 2001).

On the other hand, the completion part (Figure 16) is affected by the tax negatively, in the way that the more tax, the less completion in the IS network. It shows increasing the tax is not motivating for companies to continue synergy or add more output to the network. Costa et al. believe that taxation is not good enough to reduce the environmental impact of the industry by IS network, they postulate that other regulations such as defining standards for by-products presented in the network could be a good step to improve IS (Costa, Massard, & Agarwal, 2010).

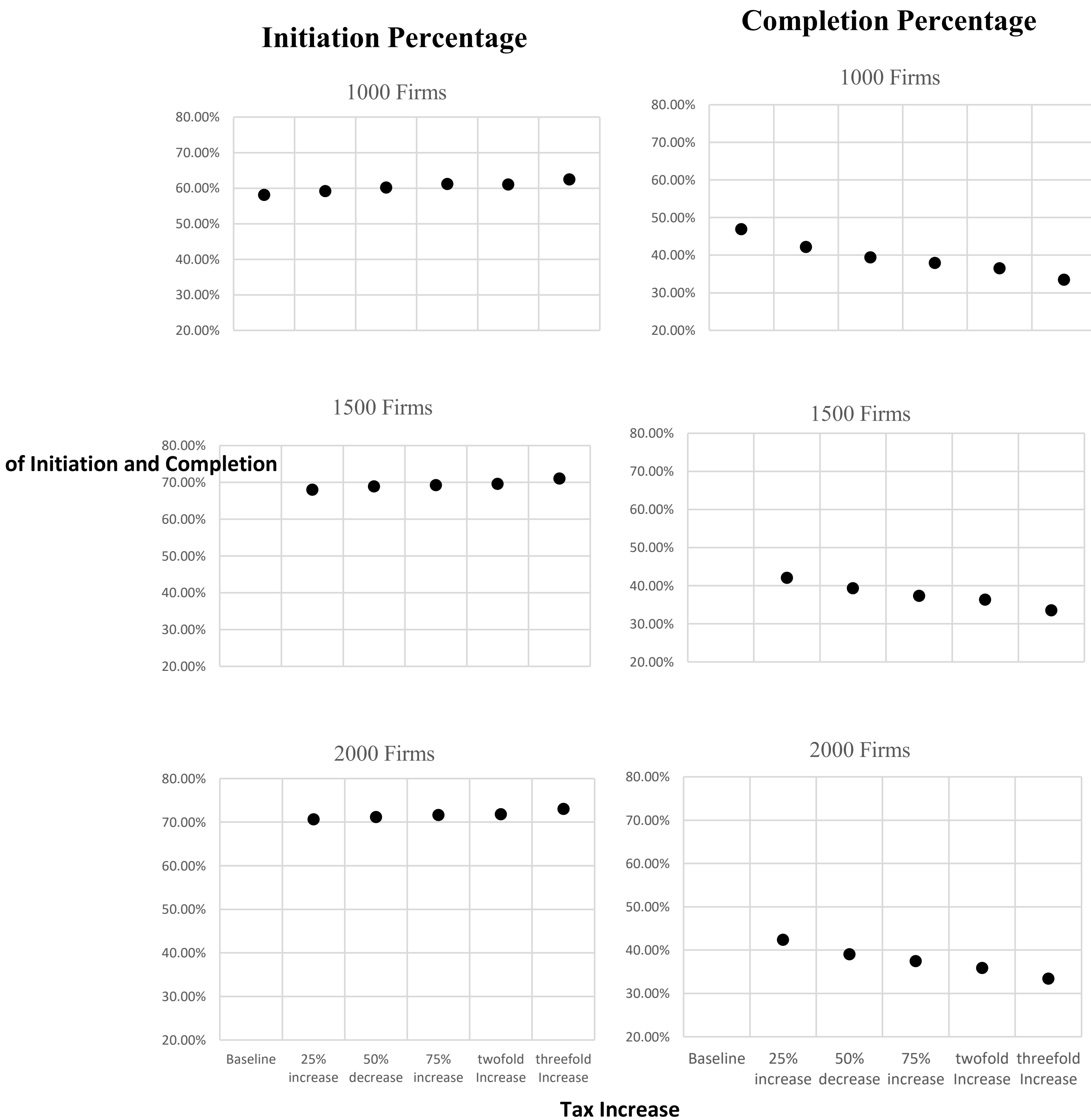


Figure 16: Initiation and completion percentage as a result of increasing landfill tax

Looking at the landfill diversion graphs (figure 17) demonstrates an increasing trend in landfill diversion which is the same trend as initiation percentage. In a deeper view of the values in table 23, you can see increasing landfill tax has a positive effect on landfill diversion in initiation. In the completion part, by decreasing the number of joint pairs the amount of landfill diversion is decreasing as well.

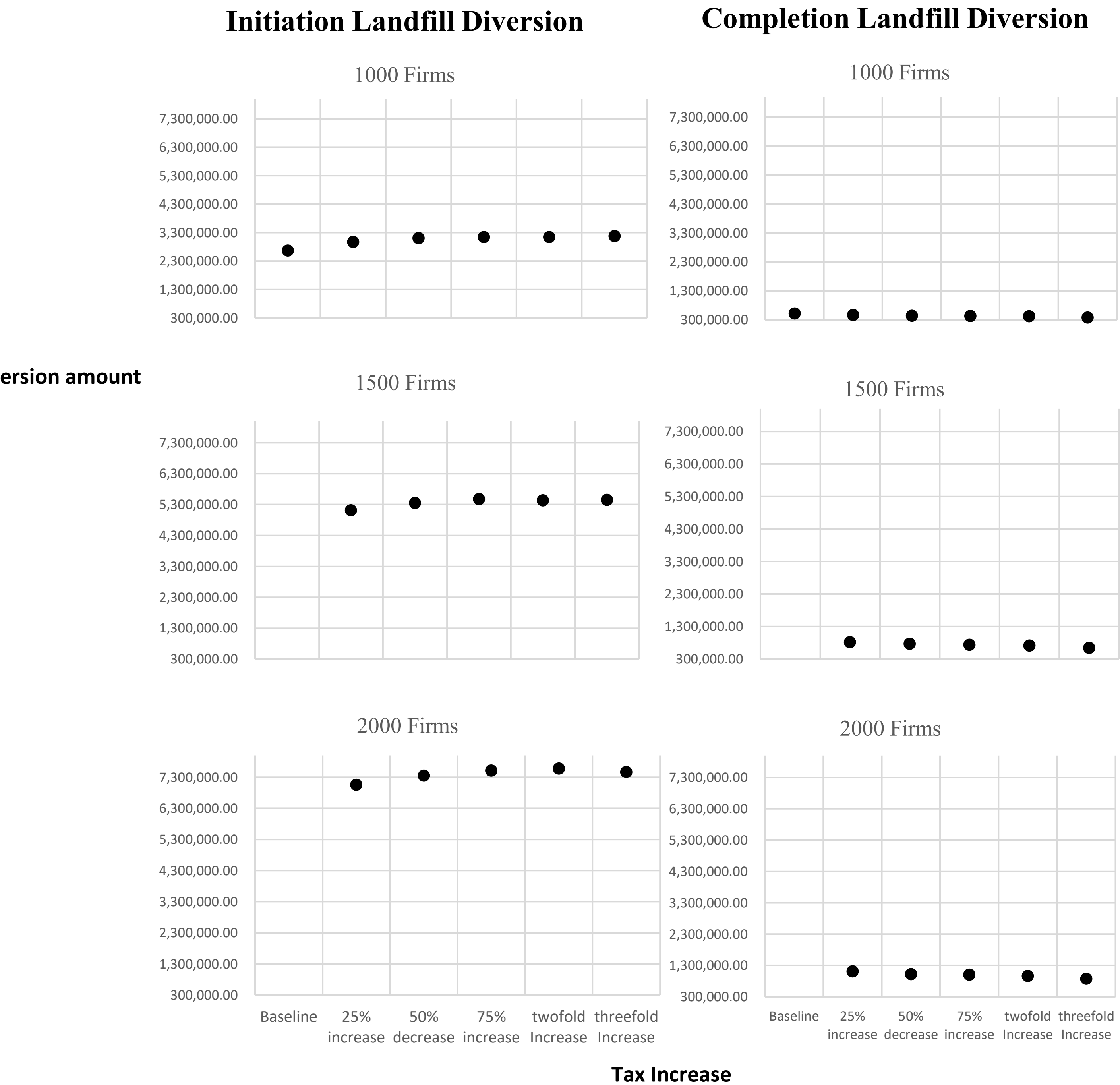


Figure 17: Landfill diversion changes as a result of increasing landfill tax

Table 23: Landfill diversion changes as a result of increasing Landfill tax

	Initiation Landfill Diversion			Completion Landfill Diversion		
	1000 Firms	1500 Firms	2000 Firms	1000 Firms	1500 Firms	2000 Firms
Baseline	2,672,172.28			518,244.31		
25% increase	2,981,301.59	5,115,484.86	7,058,035.73	468,327.18	809,217.74	1,112,708.35
50% decrease	3,114,980.75	5,353,374.64	7,351,123.58	440,916.27	765,985.15	1,029,086.91
75% increase	3,151,033.68	5,473,959.32	7,508,234.65	436,253.39	734,302.36	1,011,817.69
twofold Increase	3,149,342.04	5,435,321.55	7,575,826.36	426,944.89	714,565.96	966,779.25
threefold Increase	3,184,254.72	5,451,569.14	7,464,011.80	382,948.92	643,126.60	877,024.42

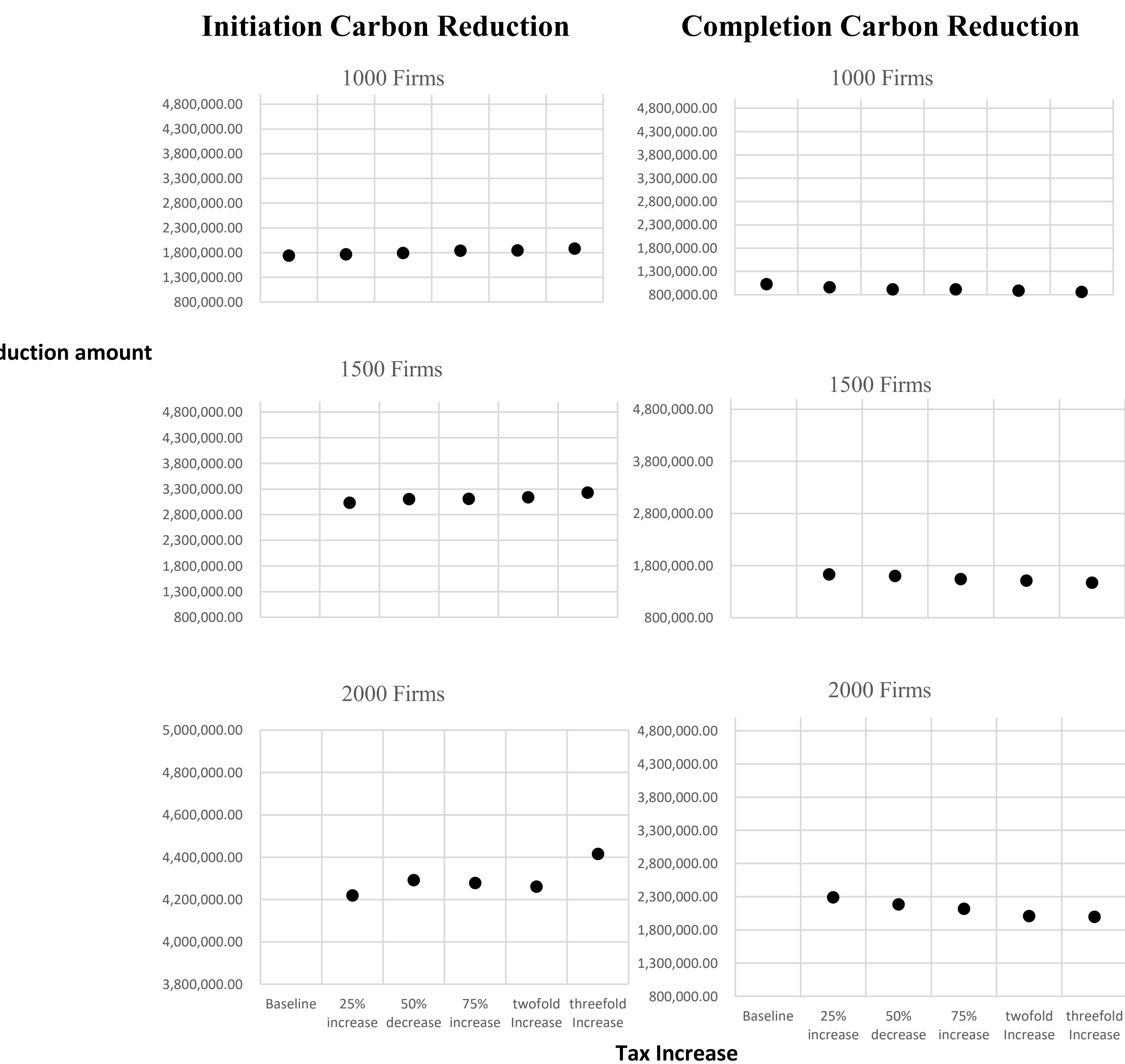


Figure 18: Carbon Reduction changes as a result of increasing landfill tax

Carbon reduction for the initiation has the same trend as initiation percentage. It is decreasing by increasing the tax in completion part and it is increasing in initiation part by increasing the tax (Figure 18). In completion part the carbon reduction amount decrease by increasing the landfill tax because of the same reason that I described in the previous paragraph for landfill diversion.

Carbon Reduction:

The result of the model for increasing the carbon tax shows an increase in initiation percentage and decrease in completion percentage. It seems taxation as a single action does not motivate firms to start synergy pointedly and in completion it is not motivating for them to have additional waste in the network or continue synergy. It seems the government should consider a package of actions or incentives to convince firms to initiate and complete in the network. In figure 19 you can see the percentage of initiation and completion in different network sizes of 1000, 1500, and 2000 firms.

As you can see in Figure 19 the general trend for initiation is increasing; however, there is not a big variation in the percentage. For example, for initiation in the network of 1000 firms, the lower and the higher percent has around two percent variation. On the other hand, you can see in the completion part the percentage of completion is decreasing; thus, it means increasing carbon tax is motivating for firms to join the network more than convincing them to continue synergy or add additional exchanges in the network.

For the landfill diversion, you can see in figure 20 that the landfill diversion trend in most cases is increasing for the initiation. However, because the variation in initiation and completion percentage are not high thus the variation in the landfill diversion is not a lot as well. The same trend exists for landfill diversion for completion part and you can see it does follow the same trend as completion percentage.

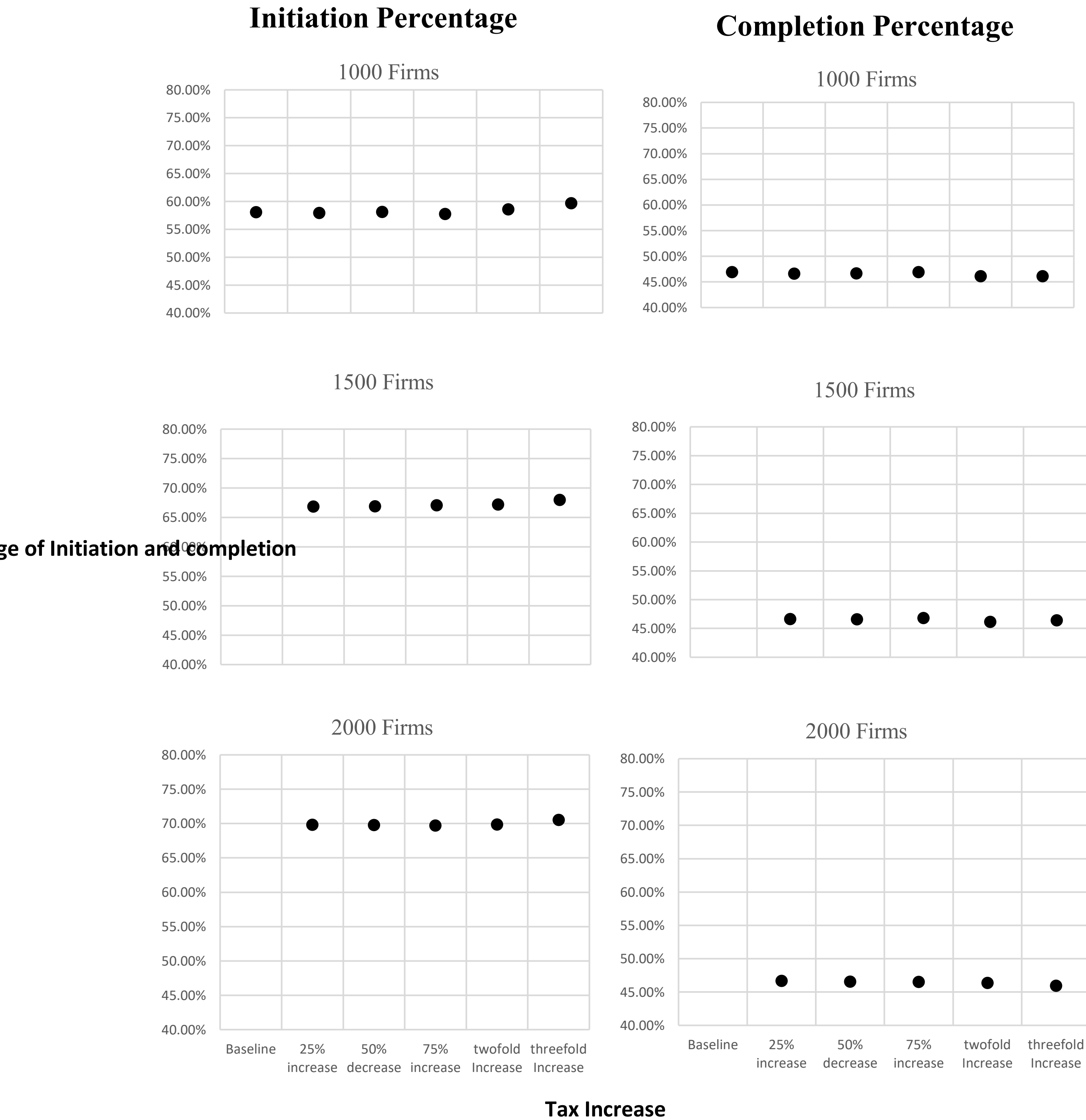


Figure 19: percentage of initiation and completion as a result of increasing Carbon tax

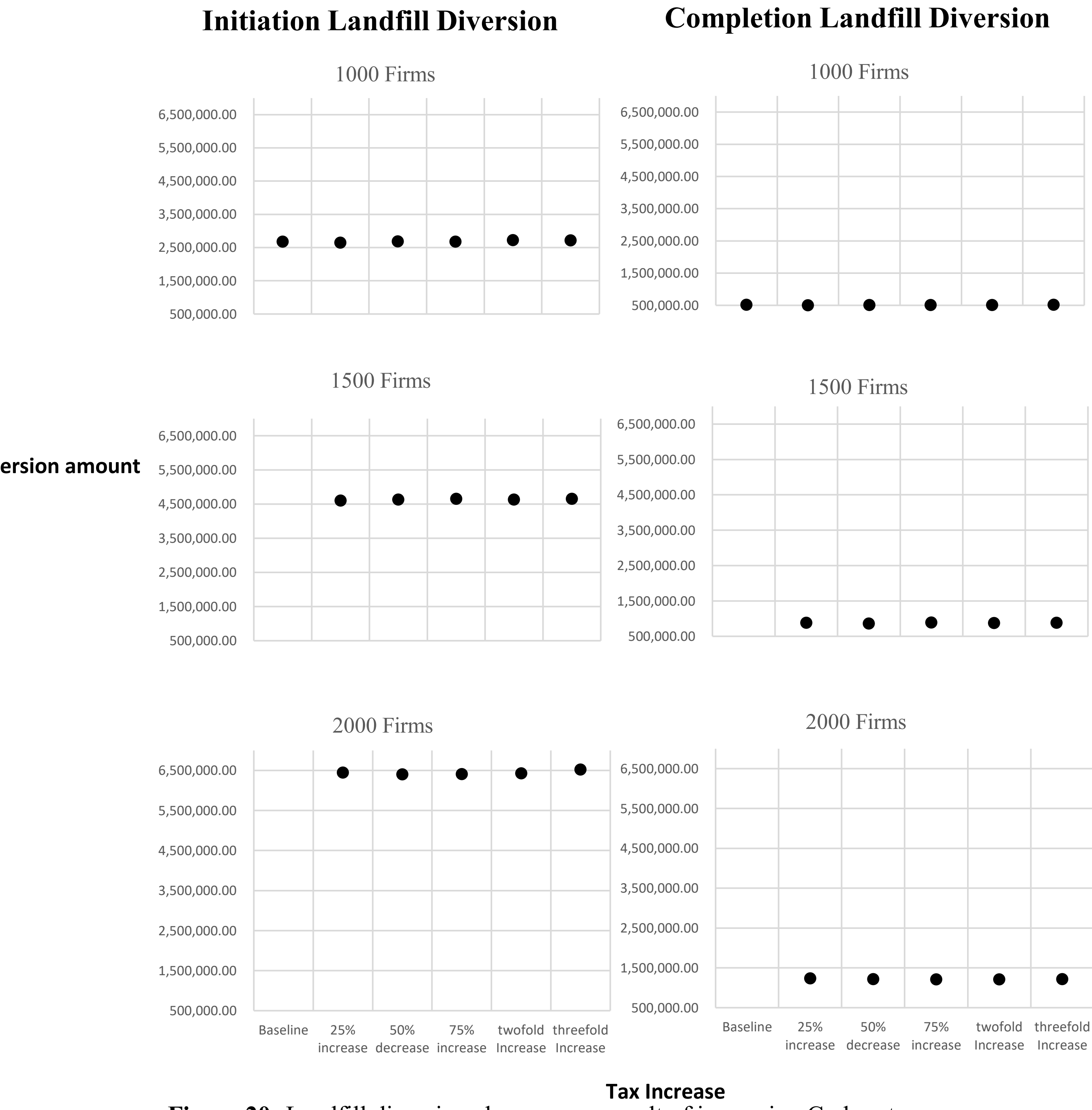


Figure 20: Landfill diversion changes as a result of increasing Carbon tax

Based on the data from the network, the amount of carbon reduction is less than landfill diversion and also the carbon tax is far less than landfill tax you can see that the network less affected by changing the carbon tax comparison to changing the landfill tax. For the initiation, you can see in figure 21 and Table 24 that the trend is increasing which follows the initiation trend. However, for completion, you can see in Table 24 and figure 21 that the increasing trend exists for the carbon reduction. It shows the even though the completion percentages decrease but firms with a higher amount of carbon tend to complete in the network.

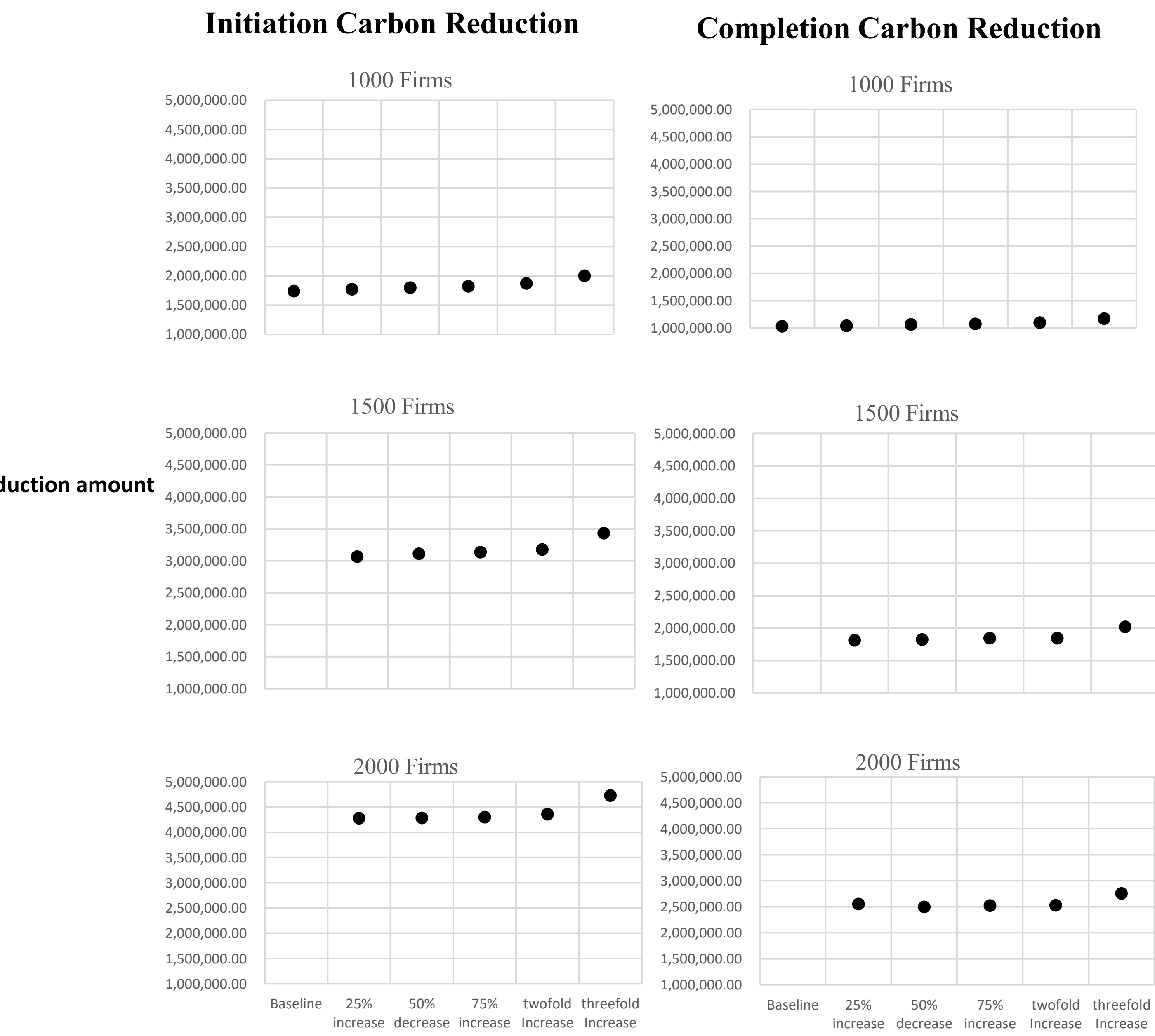


Figure 21: Carbon reduction changes as a result of increasing Carbon tax

Table 24: Carbon reduction changes as a result of increasing Carbon tax

	Initiation Carbon Reduction			Completion Carbon Reduction		
	1000 Firms	1500 Firms	2000 Firms	1000 Firms	1500 Firms	2000 Firms
Baseline	1,741,899.76			1,029,415.52		
25% increase	1,771,706.09	3,065,190.51	4,280,052.19	1,041,807.11	1,810,886.53	2,552,003.75
50% decrease	1,799,835.65	3,109,827.21	4,284,042.08	1,063,091.00	1,823,142.09	2,497,006.70
75% increase	1,823,852.50	3,135,394.84	4,301,847.57	1,075,655.54	1,844,001.34	2,520,901.09
twofold Increase	1,873,120.08	3,176,283.93	4,360,726.08	1,095,583.08	1,845,601.73	2,523,791.18
threefold Increase	2,003,178.71	3,434,401.82	4,728,354.28	1,170,640.17	2,020,668.91	2,755,379.68

Distance:

For the distance parameter, you can see in figure 22 that variation in distance between two firms does not effect on the initiation significantly and it almost stays constant. However, in some cases, you can see increasing the distance between firms reveals that the percentage of initiation is increased. It means when the distance between two firms is high the firms become more interested in coming to the IS network. On the contrary, you can see for the completion part the more distance between two firms causes the less completion percentage which means in a big city that the distances are high even though firms are more interested to become a pair with a firm which is far from them but they would not continue synergy with a far distance firm or add additional wastes to the network.

For distance variable, when you look at the objective function of initiation and completion, function (18) and (19), the distance coefficient for initiation and completion are opposite which means that one of them is positive and the other one is negative. The coefficients are reached from the real data so they show the real effect of increasing or decreasing of the independent parameter. Thus, considering the coefficients, when it multiplies by the parameter it shows that we do not have any significant changes in initiation unless the number of firms increased. The graph for initiation seems constant and it is not affected a lot by increasing or decreasing the distance between two firms. Because the number of initiation did not change as a result of having a variety of distances so the amount of landfill diversion also did not change a lot. However, in most cases, you can see in Table 25 that the trend of landfill diversion is increasing for a small amount which makes sense since we have a small increase in the percentage of initiation as well. However, in completion part, by increasing the distance between two firms, the amount of landfill diversion is decreasing which is the same trend as completion.

Table 25: Landfill diversion changes as a result of changing distance between two firms

	Initiation Landfill Diversion			Completion Landfill Diversion		
	1000 Firms	1500 Firms	2000 Firms	1000 Firms	1500 Firms	2000 Firms
Baseline	2,672,172.28			518,244.31		
25% decrease	2,625,838.00	4,552,874.07	6,341,533.36	686,560.47	1,184,811.51	1,648,034.70
50% decrease	2,691,336.12	4,574,485.75	6,299,072.08	617,359.28	1,079,786.98	1,497,160.72
75% decrease	2,611,254.44	4,600,235.13	6,386,096.51	555,390.74	960,016.00	1,342,672.79
twofold Increase	2,696,663.98	4,649,915.65	6,428,789.87	360,576.77	617,036.63	862,429.94
threefold Increase	2,698,211.89	4,584,583.05	6,479,079.86	265,091.37	469,572.93	644,342.07

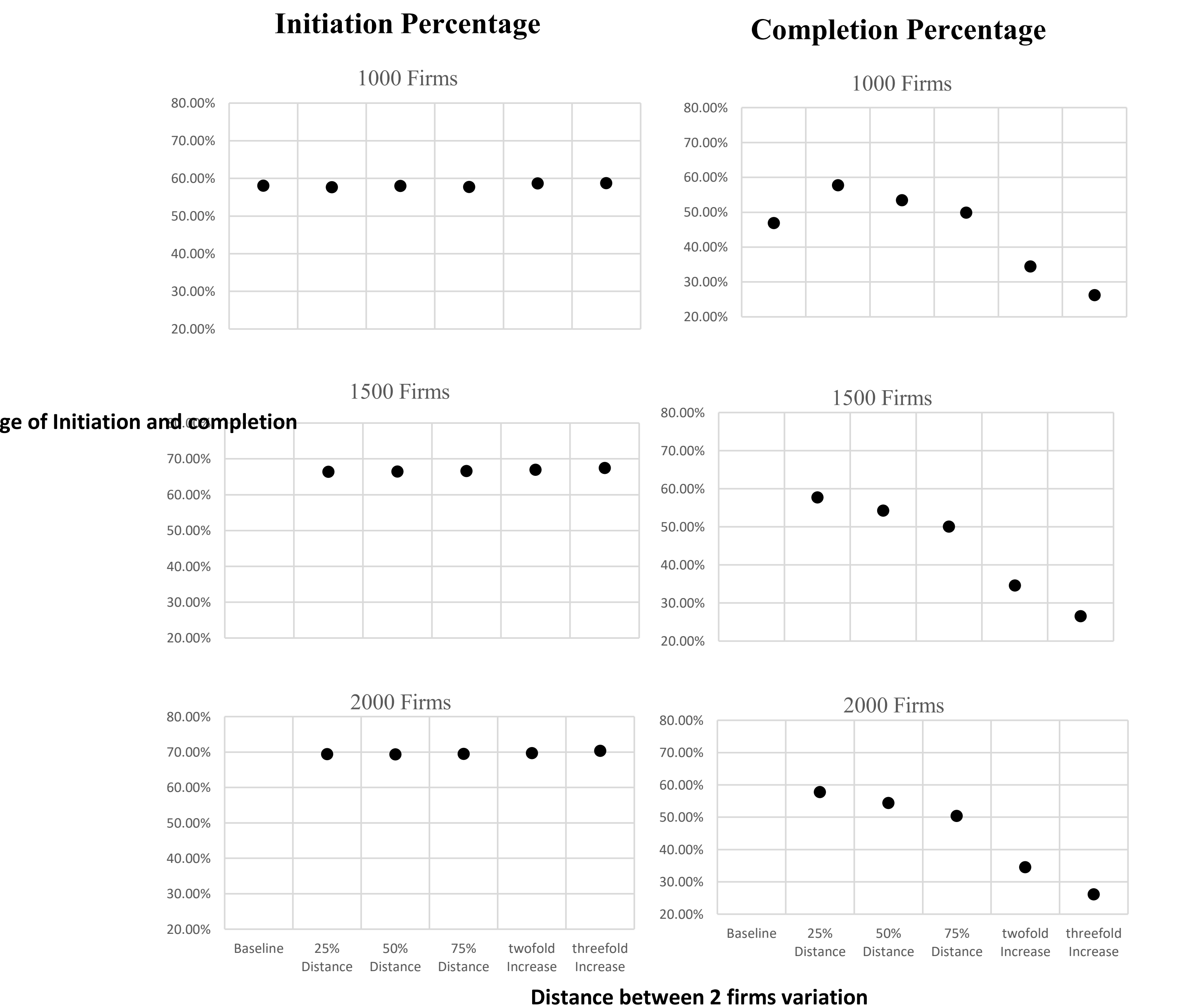


Figure 22: percentage of initiation and completion as a result of increasing or decreasing the distance between firms

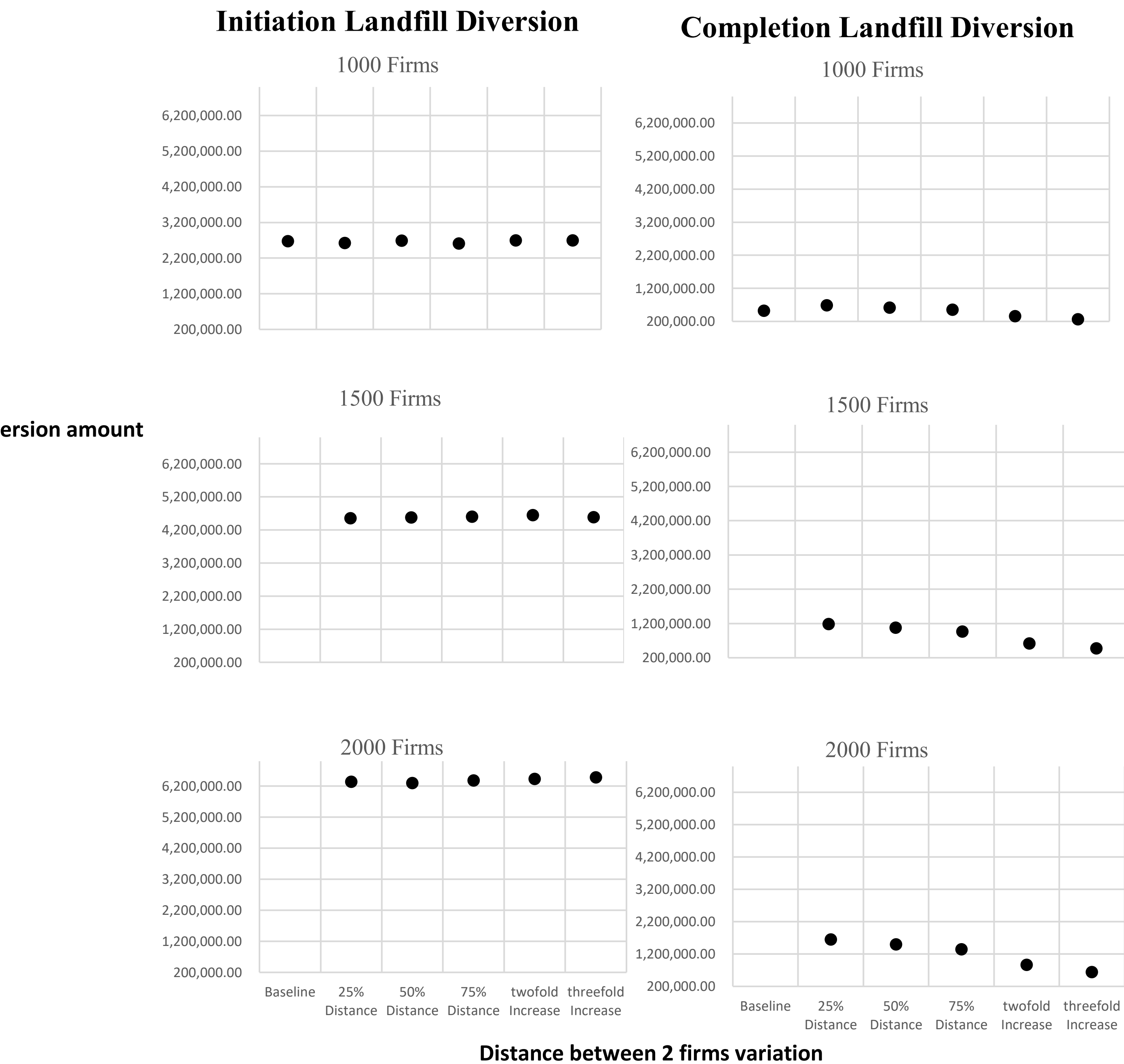


Figure 23: landfill diversion changes as a result of increasing or decreasing the distance between firms

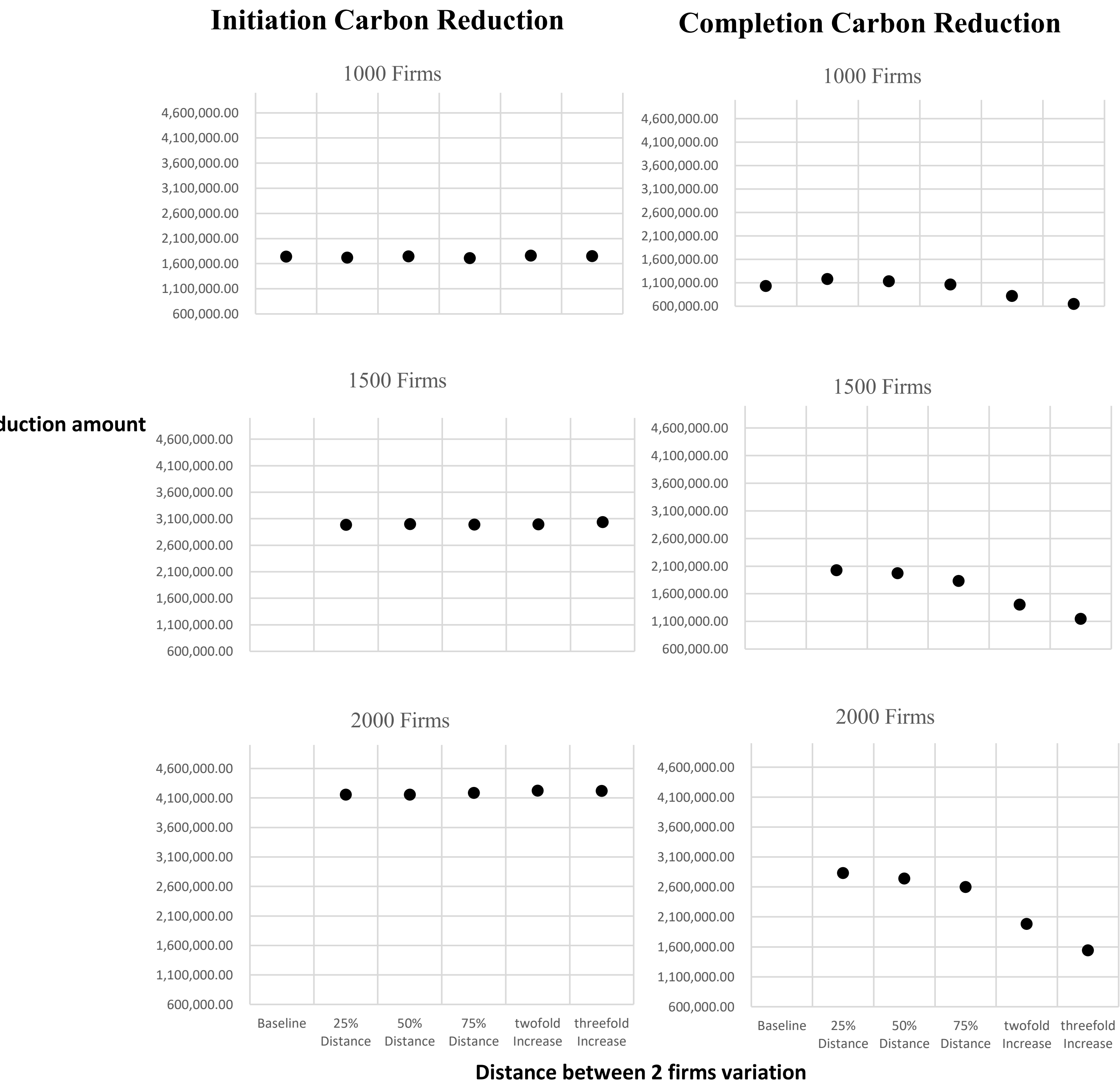


Figure 24: Carbon Reduction changes as a result of increasing or decreasing the distance between firms

$$Initiation\ Logit = (-0.309) \quad + (0.000008699\ ) *(Landfill\ Diverted) * \frac{\boldsymbol{s}_{\mathrm{x1}}}{\boldsymbol{s}_{\mathrm{Y}}} + (0.00005381)$$

$$* (age\ of\ waste) * \frac{\boldsymbol{s}_{\mathrm{x2}}}{\boldsymbol{s}_{\mathrm{Y}}} + (0.003091) *(distance) * \frac{\boldsymbol{s}_{\mathrm{x3}}}{\boldsymbol{s}_{\mathrm{Y}}}$$

$$+ (0.001376) *(\text{distance to NISP}) * \frac{\boldsymbol{s}_{\mathrm{x4}}}{\boldsymbol{s}_{\mathrm{Y}}} + (-0.000005727) * (Carbon\ reduction)$$

$$* \frac{\boldsymbol{s}_{\mathrm{x5}}}{\boldsymbol{s}_{\mathrm{Y}}} + b_6\ (\text{Cost Savings}) * \frac{\boldsymbol{s}_{\mathrm{x6}}}{\boldsymbol{s}_{\mathrm{Y}}} + (-0.000001228)$$

$$* (\text{distance to NISP})(Landfill\ Diverted) * \frac{\boldsymbol{s}_{\mathrm{x7}}}{\boldsymbol{s}_{\mathrm{Y}}} + (-0.00001622)$$

$$* (distance\ to\ NISP)(distance) \quad * \frac{\boldsymbol{s}_{\mathrm{x8}}}{\boldsymbol{s}_{\mathrm{Y}}} \quad (18)$$

$$Completion\ Logit$$

$$= (0.225) + (-0.00001127\ ) *(Landfill\ Diverted) * \frac{\boldsymbol{s}_{\mathrm{x1}}}{\boldsymbol{s}_{\mathrm{Y}}} + (-0.00005336)$$

$$* (Age\ of\ Waste) * \frac{\boldsymbol{s}_{\mathrm{x2}}}{\boldsymbol{s}_{\mathrm{Y}}} + (-0.001997) *(Distance) * \frac{\boldsymbol{s}_{\mathrm{x3}}}{\boldsymbol{s}_{\mathrm{Y}}}$$

$$+ (0.00000626) *(Carbon\ Reduction) * \frac{\boldsymbol{s}_{\mathrm{x4}}}{\boldsymbol{s}_{\mathrm{Y}}} + (0.000001091) * (Cost\ Savings)$$

$$* \frac{\boldsymbol{s}_{\mathrm{x5}}}{\boldsymbol{s}_{\mathrm{Y}}} \quad (19)$$

By looking at figure 24 you can see the same trend as landfill diversion exists for carbon reduction. The trend for carbon reduction in initiation looks constant but increased at most points. The results for sensitivity analysis for distance parameter shows lower distance affects completion more comparison to initiation.

Distance to NISP:

Looking at the "Distance to NISP" variable position in the function (18) and (19) demonstrates that it influences more on Initiation.

In the initiation part, the results reveal that by increasing or decreasing the distance to NISP the initiation rate increased slightly. However, the result of the model shows completion rate is not affected by having variation in distance of firms to NISP facilitator since the parameters is not a significant one in our function. The results show that having more distance to NISP facilitator cause more initiation in the network.

Landfill diversion rate does not change a lot for initiation part. It has slight variation by increasing or decreasing the distance to NISP facilitators and the trend is increasing. It means increasing the distance to NISP the amount of landfill diversion would increase and this increasing trend continues until it is twofold and after that, it decrease in both networks of 1000 and 2000 firms. On the other hand when you look at the result of landfill diversion for completion in figure 26 you can see it does not affected by this parameter either directly or indirectly.

Our findings also show the trend for carbon reduction changed slightly and it is almost inconsistent in most parts. However, in the initiation part, you can see that the carbon reduction is affected by increasing the distance to NISP facilitator until the point twofold.

Table 26: Carbon reduction changes as a result of changing distance to NISP facilitator

	Initiation Carbon Reduction			**Completion Carbon Reduction**		
	1000 Firms	1500 Firms	2000 Firms	1000 Firms	1500 Firms	2000 Firms
Baseline	1,741,899.76			1,029,415.52		
25% distance	1,741,026.68	2,978,505.11	4,161,389.62	1,044,791.94	1,760,208.18	2,456,779.80
50% distance	1,740,760.64	2,983,306.45	4,157,970.55	1,020,080.85	1,763,125.55	2,462,105.40
75% distance	1,741,772.89	2,992,374.54	4,152,205.87	1,019,141.07	1,750,353.02	2,438,786.93
twofold Increase	1,769,888.83	2,989,606.30	4,228,799.40	1,041,391.44	1,725,515.94	2,519,245.19
threefold Increase	1,739,348.09	3,016,616.66	4,165,534.12	1,033,284.42	1,737,793.22	2,428,738.36

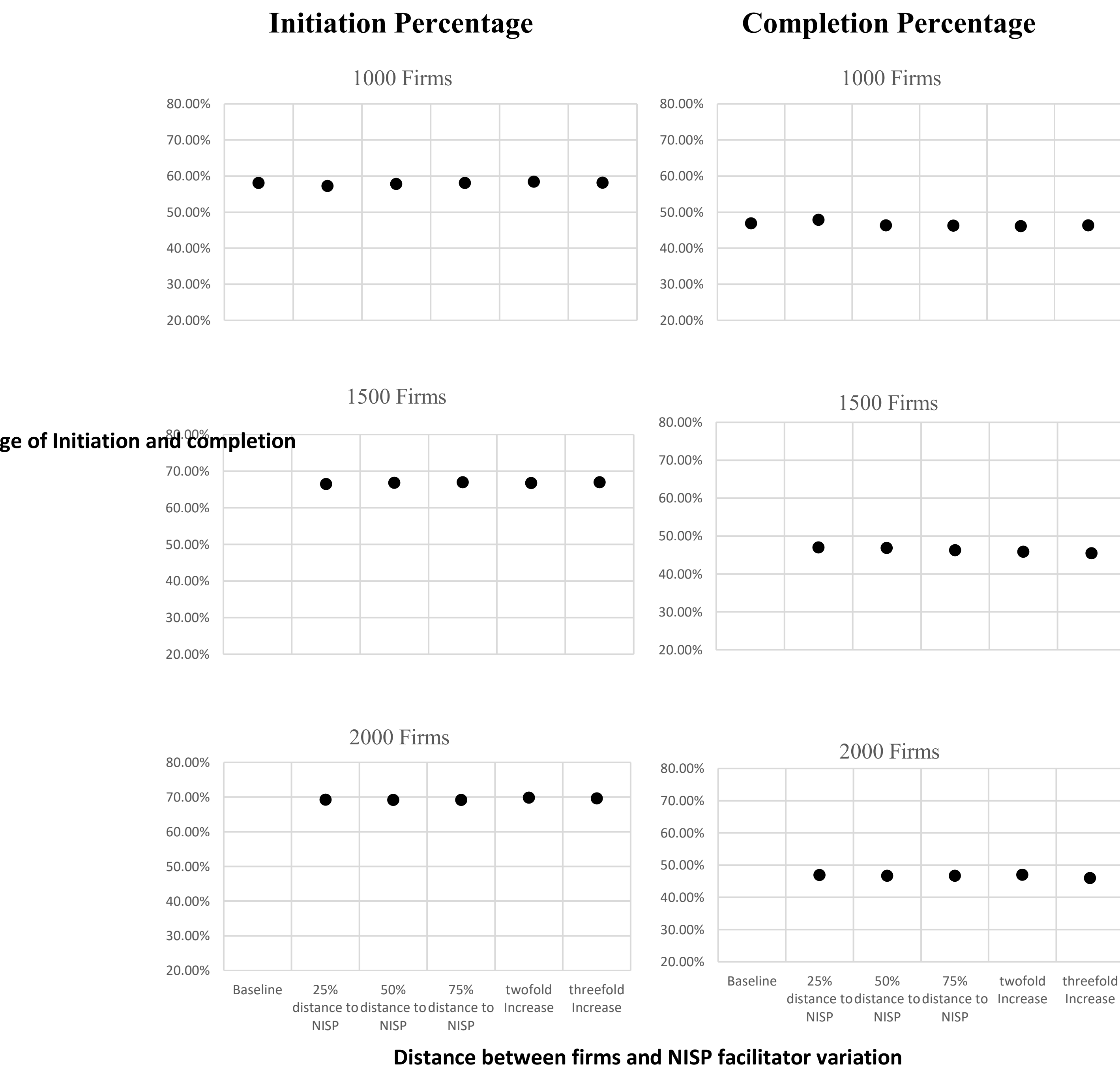


Figure 25: Percentage of initiation and completion as a result of increasing or decreasing the distance of each firm to NISP facilitator

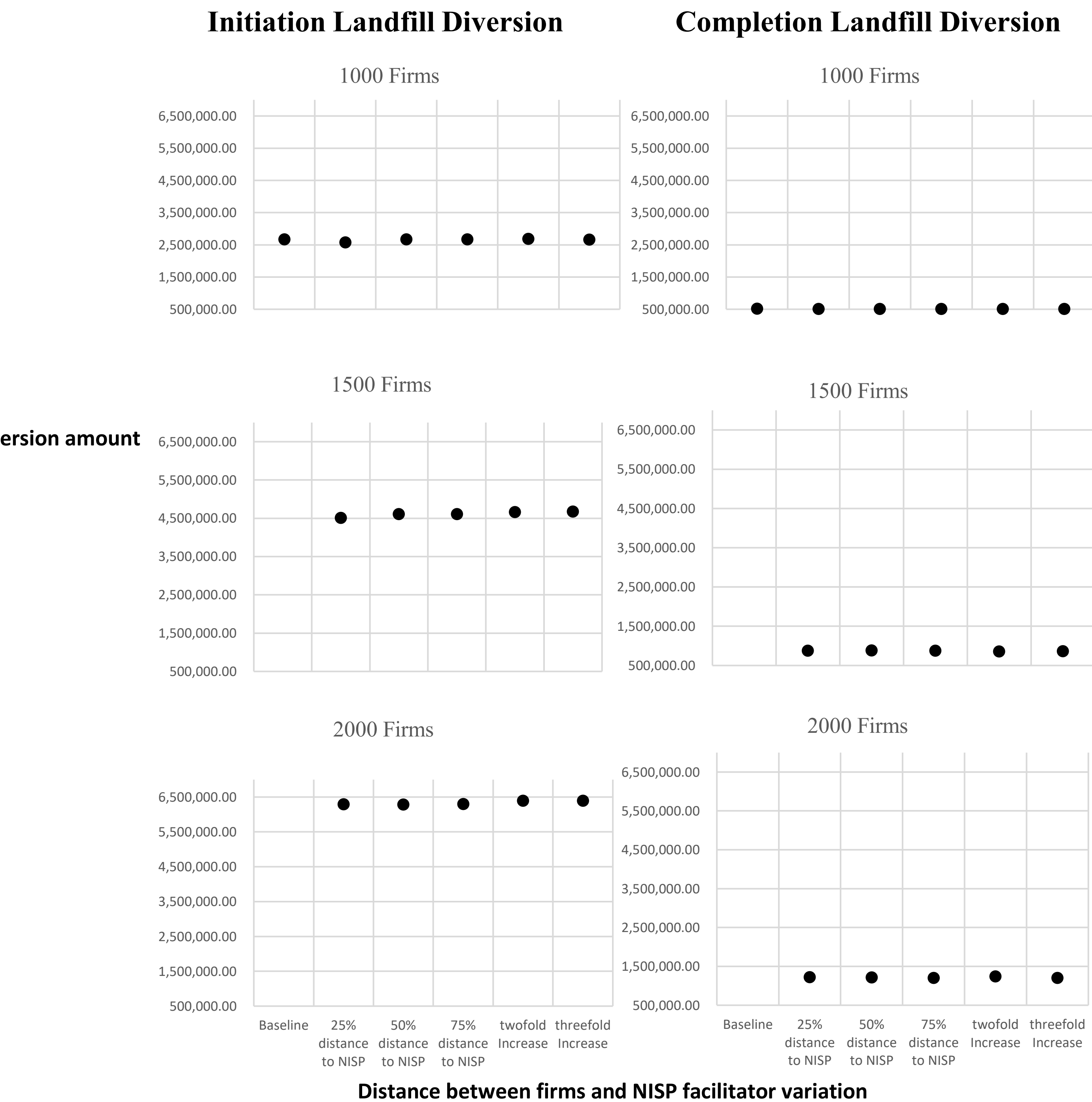


Figure 26: Landfill diversion changes as a result of increasing or decreasing the distance of each firm to NISP facilitator

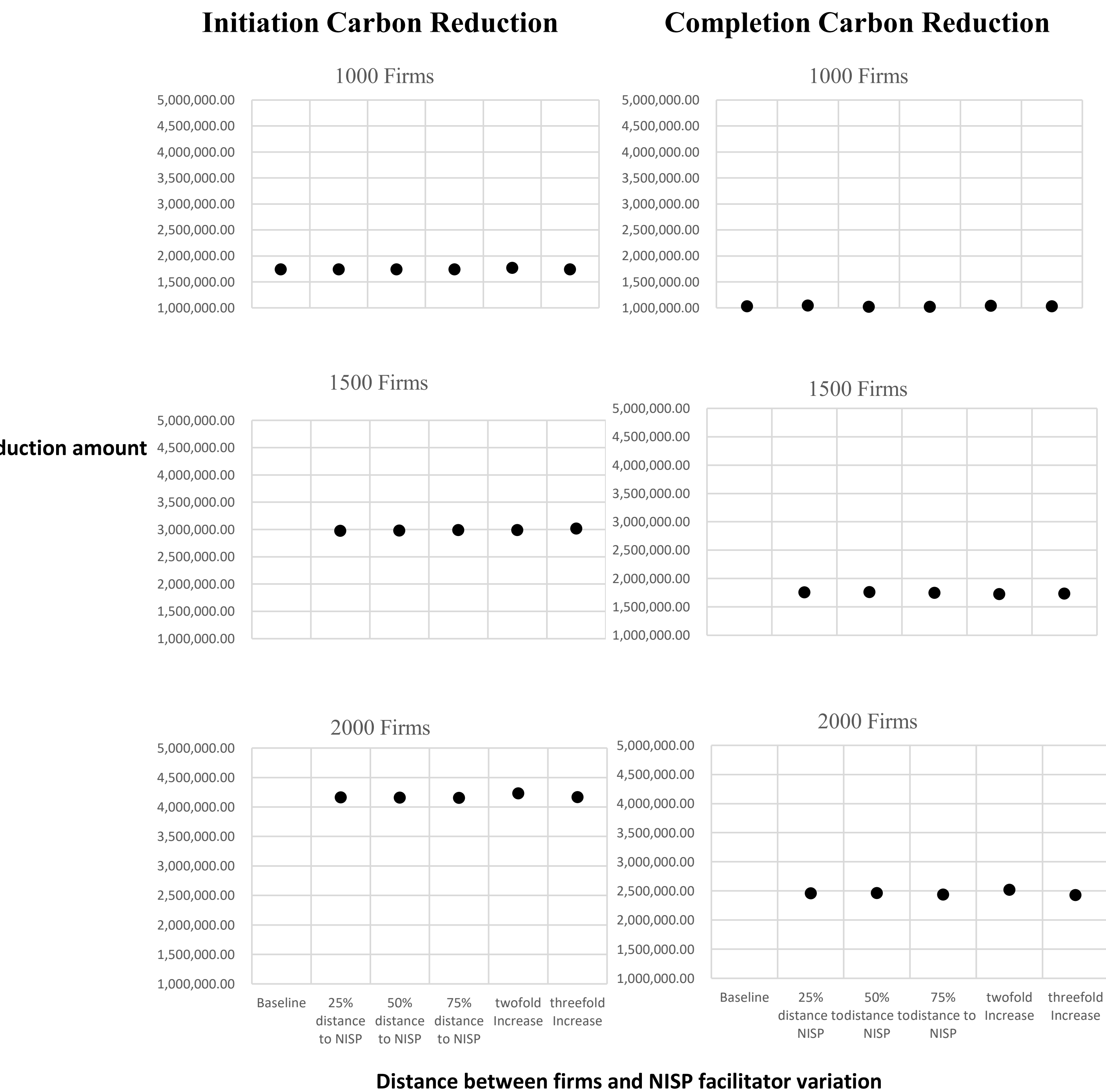


Figure 27: Carbon Reduction changes as a result of increasing or decreasing the distance of each firm to NISP facilitator

Age of Waste:

In the model result by varying the age of waste parameter you can see in figure 28 that there is an increasing trend in the percentage of initiation. It is demonstrated that by either increasing the age of waste the percentage of initiation is increased too. On the contrary, the completion part affected in all parts which demonstrate that the less aged waste the more completion in the network. So in the other word, more firms incline to continue cooperation in the network or add additional exchanges by having less aged wastes.

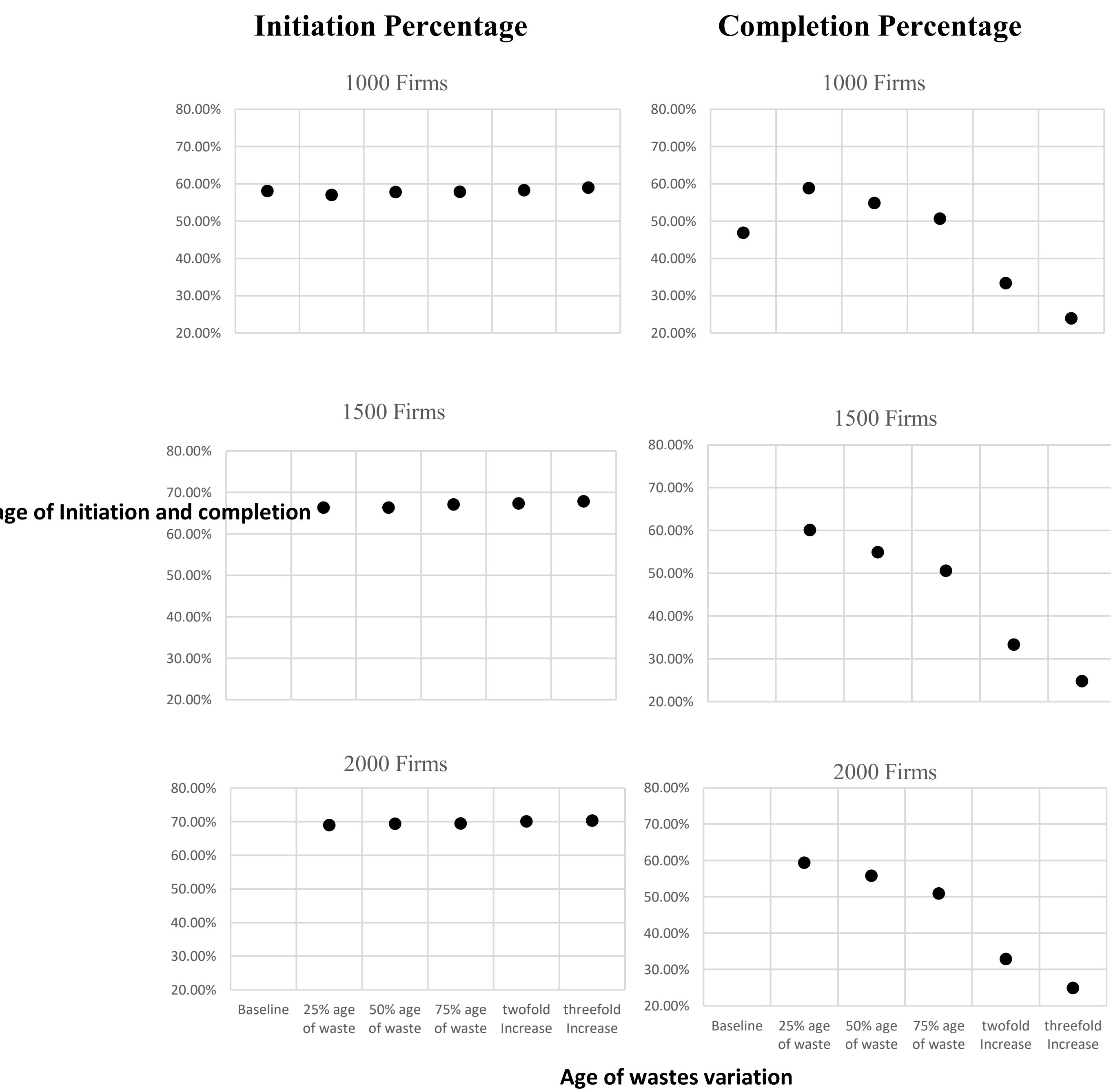


Figure 28: Percentage of initiation and completion as a result of increasing or decreasing the age of waste in the network

The landfill diversion for initiation also follows the same trend as initiation and it gets higher when we have more initiation by increasing the age of waste. On the other hand, the Landfill diversion for completion part increased when we have less aged waste in the network. You can see the landfill diversion variation in figure 29.

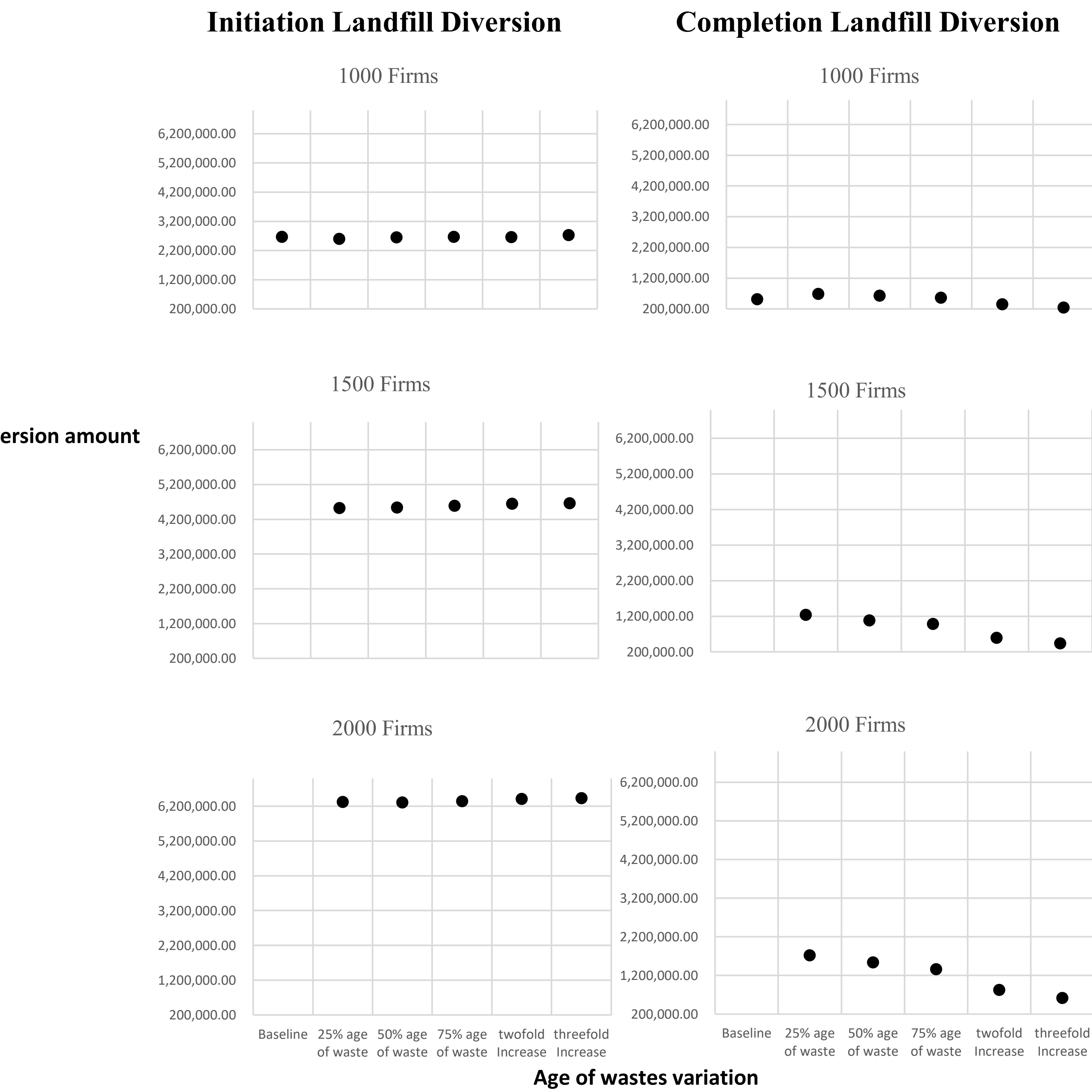


Figure 29: landfill diversion changes as a result of increasing or decreasing the age of waste in the network

In figure 30 Carbon reduction also keeps the same trend as initiation and landfill reduction has and it increases when we have a greater age of waste. Carbon reduction also follows the same trend as completion percentage. In the other word, as the waste is less aged the completion percentage will be higher and the landfill diversion and carbon reduction amount would be higher as well.

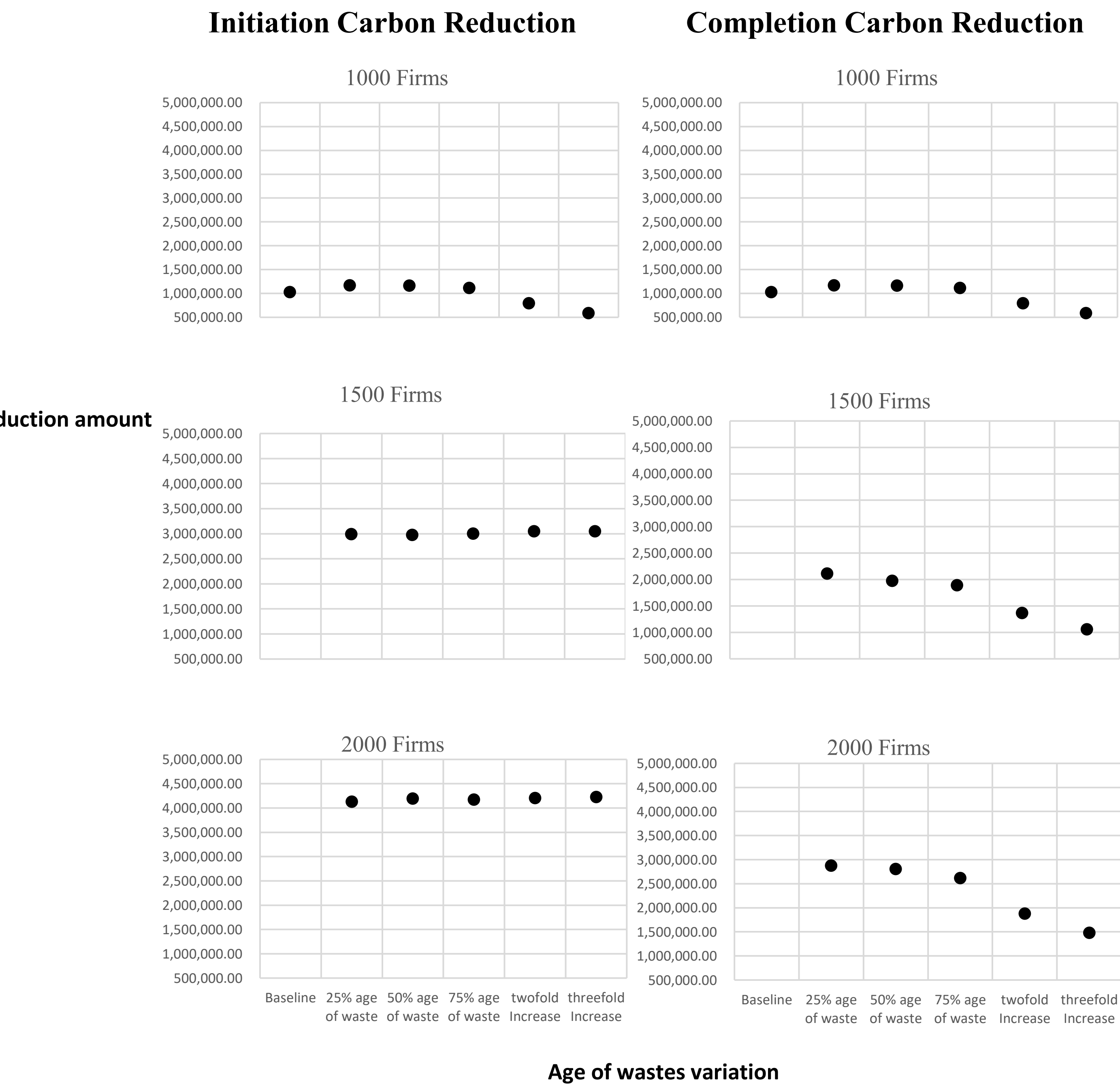


Figure 30: Carbon Reduction changes as a result of increasing or decreasing the age of waste in the network

6.4 Trust Analysis:

Industrial symbiosis stands out as a way to improve economic, social and environmental conditions simultaneously. Trust is a key component of encouraging firms to work together. For example, Stacchini (2015) in his research asserts that family businesses because of having more trust in their networks has lower agency cost comparison to the regular businesses which there is a lower level of trust in the environment. Because of the trust level in family businesses banks also consider a discount for their loans when the loan wants to go to a family network and in this way, the threat of confiscation will be eliminated (Stacchini & Degasperi, 2015). While trust and participation of firms in IS or IE networks could occur naturally, evidence suggests that more effort needs to be made to increase trust in order to improve IS participation. To make this point clearer, Dhersin et al. (2004) argue that even in R&D sections if there is a cooperation between different R&DS in different companies, if there exist enough trust between them the collaboration will be more successful. They divide the network into two categories, which name non-opportunists and opportunists and analyze these two groups in different cooperation combination such as opportunists and opportunists, non-opportunists and opportunists, etc. and finally, they resulted that in the situation of the low-level trust there would be no initiation when one of the partners are non-opportunist no matter how much profit the initiation could have for them (2004). And there could be initiation when both of the partners are non-opportunist (2004). They also concluded that the collaboration could be satisfactory or unsatisfactory for the cases that two opportunists initiate with a high level of profit and with the pair of one non-opportunist and one opportunist or two opportunists with a low level of profit; therefore, with a high level of trust in the network even though the profit is not high R&D alliance would happen (Cabon-Dhersin & Ramani, 2004). Significant barriers to IS exist, for reasons that are "technical, informational, economic, regulatory and motivational". Gibbs (2003) claims that all of these barriers can be solved by having more trust in the network because companies would be less reluctant to share information about their processes or their final products if they trusted other companies more. Gibbs (2003) believes that creating connections between firms can solve the infrastructure problems however because of the scarcity of the research, there are lots of questions about the environmental, economic and social profits developments that can be caused by applying Industrial ecology (Gibbs, 2003). Dunn et al, also believes that the synergy improvement in such a network is based on the trust and a long-term personal relationship(Dunn & Steinemann, 2017).

Ghali et al. (2017) discuss different ways that industrial symbiosis networks improve and they imply that trust plays a key role in this regard. They also used agent-based simulation for their trust analysis and considered firms as agents in their model (2017). In the model, they considered different social attributes, values, and levels of knowledge for each firm (2017). They considered trust as an attribute of a directed social contact instead of considering it as the attribute of the formal plants contact (2017). They considered minimum and maximum of -1 and 1 for the trust variable in their function(Ghali, Frayret, & Ahabchane, 2017).

Here in our simulation model, we considered trust variable (T) as a binary variable. Recalling our objective function (20) for the agent-based simulation the pairs (include two matched firms) considered as an agent; thus, we considered 1 for a pair which has trust between its firms and 0 for a pair which does not have trust in their firm's relationship (Function 24). We also analyze reducing the trust in the network and in this regard we considered -1 for firms that they lose trust and 0 for the rest (Function 25).

The initiation logit in our probability function is a logistic regression and because we do not have data for trust in our dataset we cannot consider that in our function as a binary value. For considering trust in the logit function we separated the function into two parts of the logit function of existed parameters (function 26) and the trust function (function 21). Thus we need some kind of coefficient to examine the effect of trust parameter on our dependent variable. Ashton analyzes the relationship of the trust and industrial symbiosis (2008). Based on her studies the Pearson correlation coefficient (Function 23) between trust and industrial symbiosis is 0.129 and we keep this value as trust coefficient in our logit function (Ashton, 2008).

Based on European data, trust between individuals is lower than trust between people and police and trust in the political system ("Trust," n.d.). The data for the United Kingdom specifically quantifies trust at 29% and 30% in 1998 and 2009 and this number is based on survey data which individuals were asked if they agree or disagree with the statement "most people can be trusted"("Trust," n.d.). However, because our network targets only companies we need the trust level between them. Lau and Rowlinson evaluated the trust between construction companies and their data analysis shows that between corporations which are not partners the trust level is 50% (Lau & Rowlinson, 2009).

Cavalcanti et al. believe that by increasing the relationship between firms the trust level will grow thus we consider this in our model in the way that at the beginning of each season the trust will be updated in our model (Cavalcanti, Filho, & Ceglia, 2017).

Therefore we evaluate the IS network with the 50% baseline and progressively add 10% points of trust through 100% and also decrementing toward 0% and then we evaluate the results by examining initiation and completion numbers and percentage, landfill diversion, and carbon reduction.

$$Initiation = \frac{1}{1+e^{-logit}} \qquad (20)$$

$$\begin{aligned} &Initiation\ logit \\ &= f(\ (Landfill\ Diverted), (Age\ of\ Waste), (Distance), (\ Distance\ to\ NISP), (CO_2\ Reduction), (Cost\ Savings)) \\ &+ f(Trust)\ (21) \end{aligned}$$

$$f(Trust) = Pearson\ Correlation\ Coefficient * T \qquad (22)$$

$$f(T) = \frac{COV(X,Y)}{\sigma_x \sigma_Y} * T \qquad (23)$$

$$T = \begin{cases} 1, & Having\ Trust \\ 0, & Otherwise \end{cases} \qquad (24)$$

$$T = \begin{cases} -1, & Not\ Having\ Trust \\ 0, & Otherwise \end{cases} \qquad (25)$$

$$\begin{aligned} &f(\ (Landfill\ Diverted), (Age\ of\ Waste), (Distance), (\ Distance\ to\ NISP), (CO2\ reduction), (Cost\ Savings)) \\ &= b_0 + b_1(Landfill\ Diverted) * \frac{s_{x1}}{s_Y} + b_2(age\ of\ waste) * \frac{s_{x2}}{s_Y} + b_3(distance) * \frac{s_{x3}}{s_Y} \\ &+ b_4(\text{distance to NISP}) * \frac{s_{x4}}{s_Y} + b_5\ (CO2\ reduction) * \frac{s_{x5}}{s_Y} \\ &+ b_6\ (\text{Cost Savings}) * \frac{s_{x6}}{s_Y} + b_7(\text{distance to NISP})(Landfill\ Diverted) * \frac{s_{x7}}{s_Y} \\ &+ b_8(distance\ to\ NISP)(distance) * \frac{s_{x8}}{s_Y} \quad (26) \end{aligned}$$

Initiation

Increasing the trust in the network resulted in an increase in the number of initiations in IS. We increased the trust percentage by 10 percent and we get the level of 60 percent for trust. In figure

31 in the level of 60%, you can see that the number of firms that could initiate an increase in comparison to our baseline scenario. We increase the percentage of trust up to 50 percent which the level of trust would be 100% and at this point, 627 firms are initiated. By increasing the number of firms through the network we have more firms that they can find their matches in the network. So, we would have more firms that they can initiate. In figure 31 for initiation, you can see that 1061 firms out of 1500 firm initiate.

In figure 32, you can see the percentage of initiation having 1000 firms in the network by increasing trust percentage the percentage of initiation also increased up to 62.71%. Increasing the number of firms in the network makes a jump in each percentage of trust. At the final point increasing the number of firms to 2000 and the trust percentage of 100% you can see that the percentage of initiation is 72.62%.

By having more initiation in the network the amount of landfill diversion also increased in most cases (figure 33). However, in some cases, the amount of landfill diversion decreased a little which is because of randomness in the simulation model. For some cases that everything is fine for initiation but the manager or responsible people decide not to come to the network. In this case, our perception out of this happening is that although increasing trust causes more initiation in the network; but, sometimes some pairs initiate with a small amount of the landfill which makes a little decrease in the landfill diversion.

The same thing happens for the carbon reduction in the network (figure 34). In most cases, the amount of carbon reduction increased but in some cases, you can see the amount of that decreased for a little which is again the effect of randomness in the network. Because of the percentage of initiation slight increases in these levels, therefore, the effect of randomness and peoples decision causes the decrease in the carbon reduction factor.

By decreasing the trust level in all networks you can see the decreasing trend in the percentage of initiation landfill diversion and carbon reduction. Thus the initiation stage is influenced by increasing or decreasing the trust level significantly.

Completion

On the other side of our research, we have the completion part which is affected a lot by having more trust in the network. Looking at the first graph give you some information about the number of firms that could complete in different stages of trust (Figure 31). The number of initiated firms changed from 274.36 to 372.52 when the trust level increases for 10%. Bearing in mind that the completion in the network with 1000 firms would be out of the number of firms which are already initiated. This is because only initiated firms have the chance to complete in the network. Thus in the first case increasing the percentage of trust causes 372.52 firms to complete which the number of completions is out of 591.8 initiated firms and it gives us information that the completion percentage increases about 15.79% and from 47.15% it is now 62.95% (Figure 32).

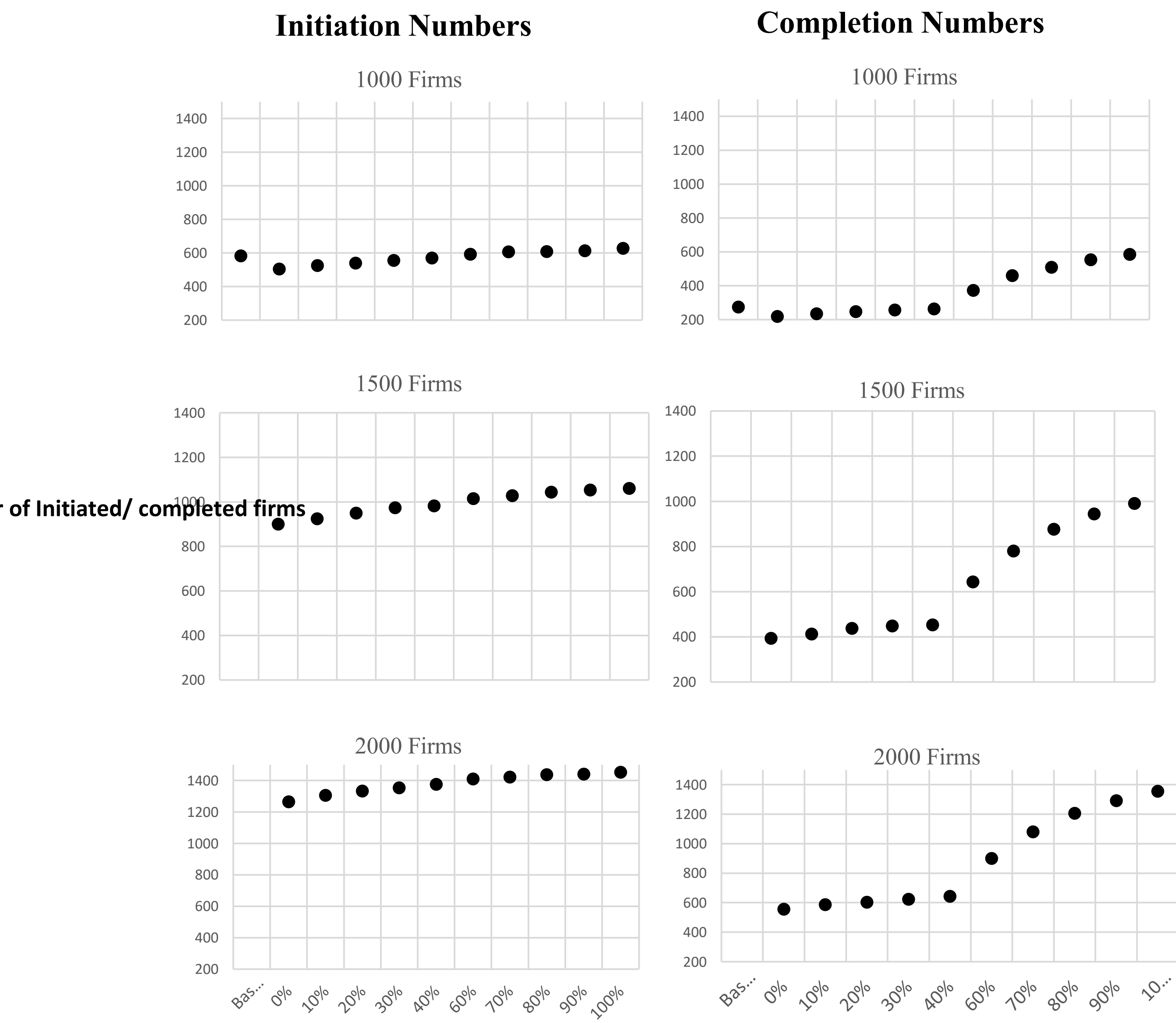


Figure 31: Initiation and completion number of firms changes as a result of increasing Trust level in the network

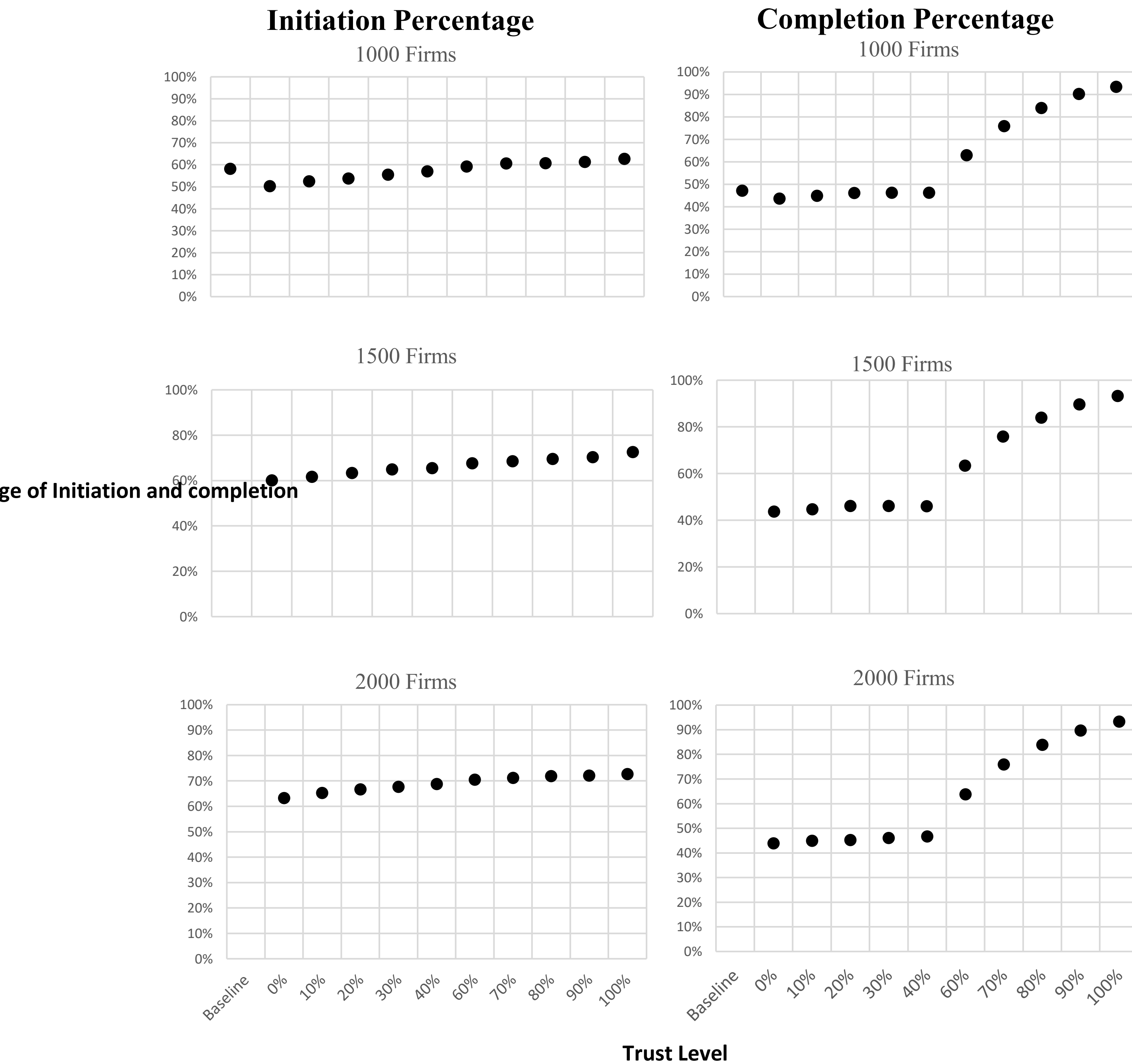


Figure 32: Initiation and completion percentage as a result of increasing Trust level in the network

By increasing the number of completion in the network the amount of landfill diversion increases as well. Because of having a noteworthy increase in completion percentage the landfill diversion amount is also increased significantly. For example in the first graph in Figure 33 for completion which is for the network including 1000 firms when the trust level increased for 10% the landfill diversion increases 432,811.98 and at the end, in the level of 100% trust, the amount of landfill diversion gets 2,170,428.60 which shows 1,692,034.82 increase from our baseline scenario. Finally, you can see in the following graph that the general trend in landfill diversion is increasing. The same trend exists for the carbon reduction amount which is one of the important parts either in our research or for the environment. In Figure 35, completion part, you can see except for two cases the rest of the cases are increased as a result of increasing the trust percentage. First I want to mention the cases which are increasing, by increasing the completion percentage it is obvious that more prevention would happen in line with emitting carbon to the environment. However, because of randomness, in two cases you can see (Figure 34) carbon reduction does not increase. In these cases, some pairs with less carbon have the chance to continue synergy in the network, in these cases while we have an increase in completion percentage the emission of carbon does not decrease. So you can see a decrease in carbon reduction level at these points at the graph. However, the general trend in the graph shows an increase in carbon reduction amount by increasing the trust level.

By decreasing the trust level you could see the completion does not affect the same trend as increasing trust. It gives us a clue that the firms that already started synergy together it is less probable to lose the trust later. So you can see when the trust decreased even though fewer firms initiated but there from those initiated firms a few numbers of them stop synergy or adding additional wastes.

The extra definition of initiation part

For the initiation part, I would like to add extra definition to the results of this part. As you saw for initiation results (figure 31&32), increasing trend was not significant even when we had the level of 100% trust. Another problem with the initiation percentage result is that for lots of cases by increasing the trust level we did not see any changes in the initiation percentage (figure 32). For example, in the network with 1500 firms by increasing trust percentage from 90% to 100% and also from 80% to 90% in figure 32 you can see one percent increase in initiation percentage and also when trust level from 90% increases to 100% there is just a small increase in initiation. So we decided to have a deeper view of the model which shows in figure 35. The reason for having different percentages in this graph comparison to the previous initiation graph (figure 32) is that in each group of waste there are some firms that they can find their matches. In our model, we consider all of the different combinations of the firms. So one firm can be in five pairs. Sometimes all of these five pairs or most of them can potentially initiate; however, just one of them can initiate in the model and the rest of them will be deleted from the simulation model. This is something that the data does not include. Therefore, by considering all of those potential pairs we reach the figure 35 which shows a significant increase in almost all cases.

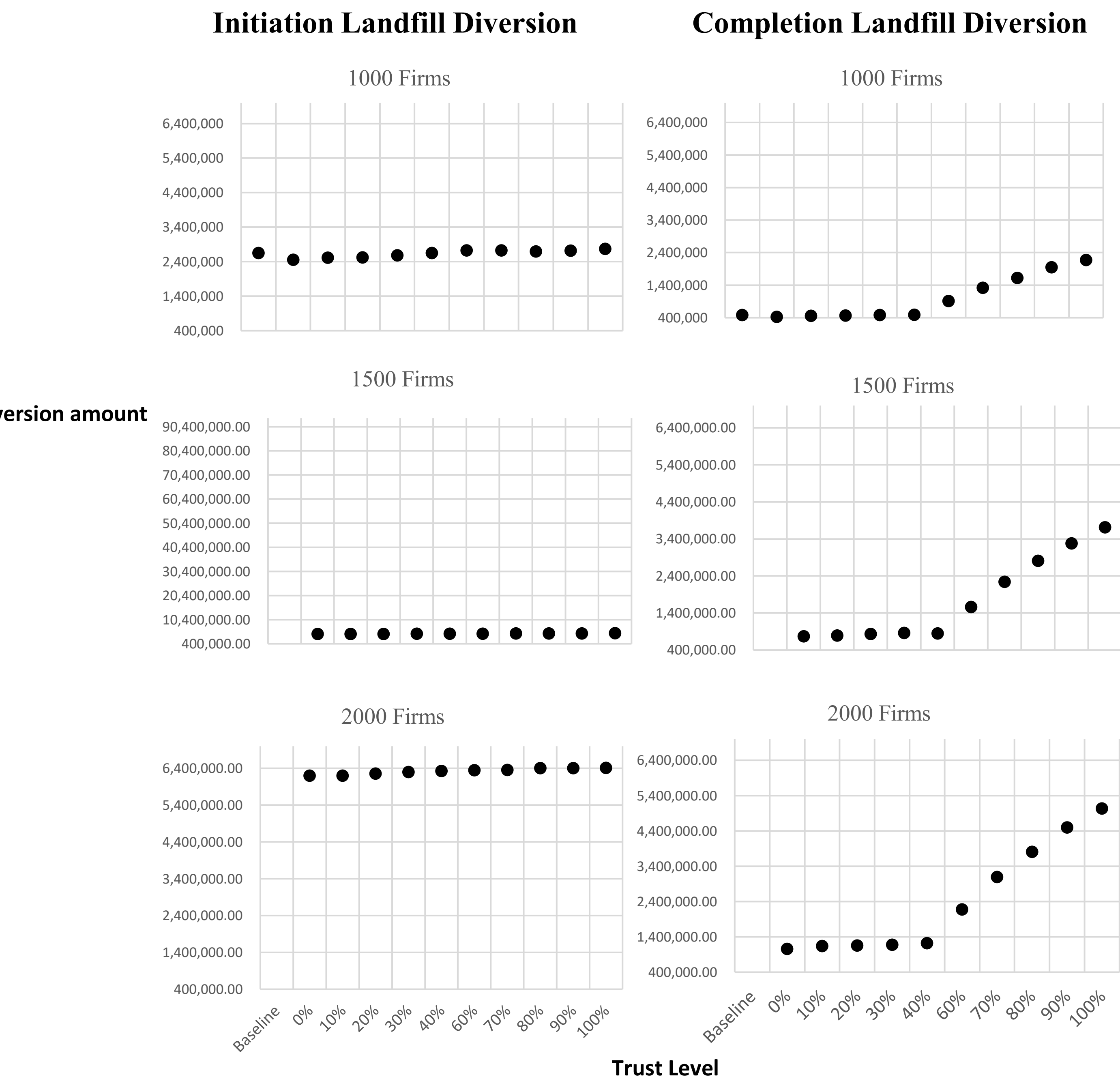


Figure 33: Landfill Diversion changes as a result of increasing Trust level in the network

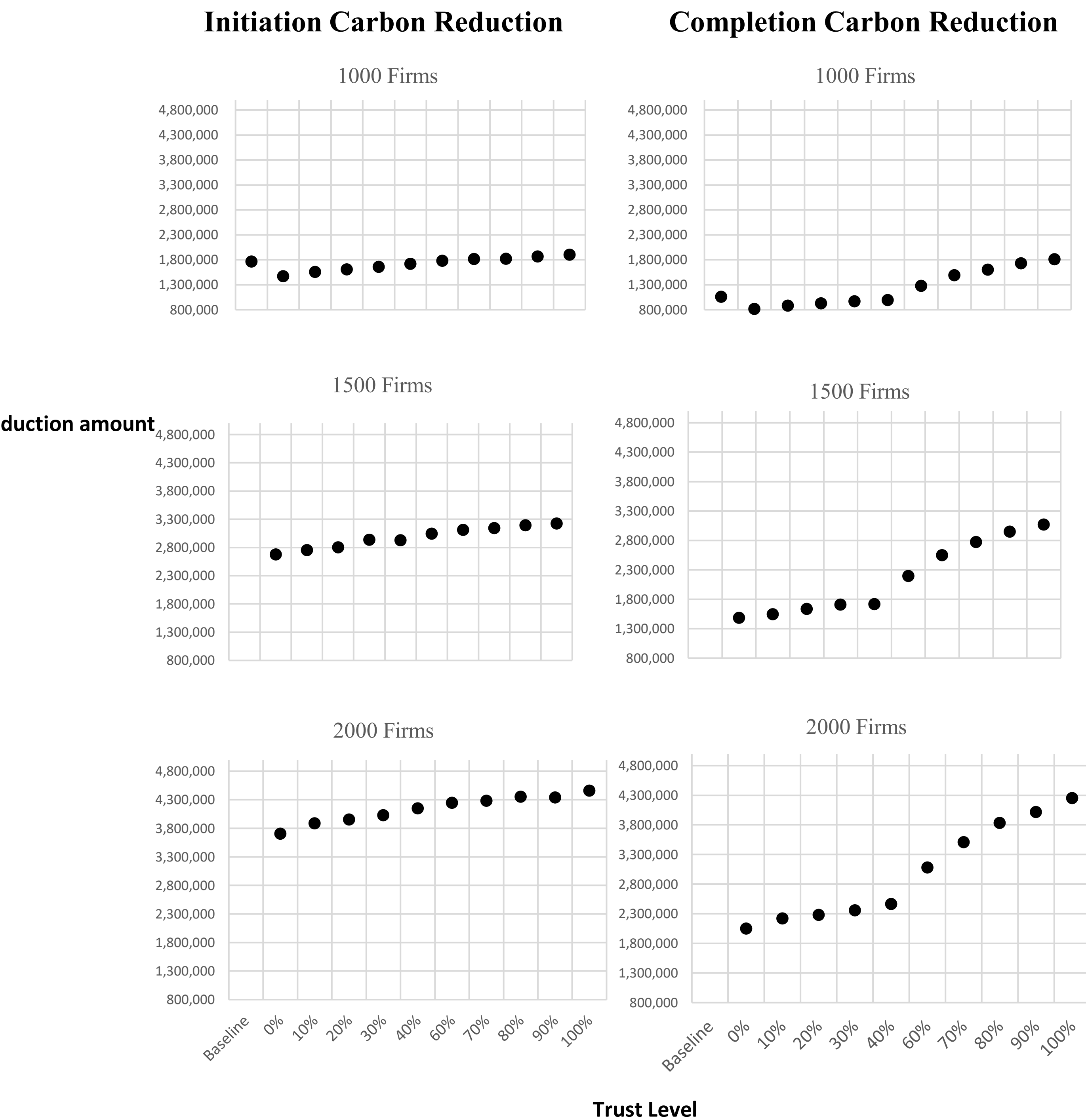


Figure 34: Carbon Reduction Changes as a result of increasing Trust level in the network

By increasing the percentage of initiation you can see in figure 36 that the amount of landfill diversion increased significantly. In our baseline scenario, the amount of landfill diversion is 15,780,521.45 which is increased to 17,146,058.88 by increasing trust for 10 percent and it means that it is increased 1,365,537.43 comparisons to the previous situation. The increasing trend continues until it gets 22,503,148.34 in the network with 1000 firms which means 6,722,626.89 increase from the baseline scenario and in trust status of 100%, by growing the number of firms to 1500 and 2000 we have the landfill diversion of 53,274,620.63 and 88,116,908.72 respectively.

Incrementing initiation percentage also affect carbon reduction which causes it to increase expressively. As you can see in Figure 37 and Table 27 the amount of carbon reduction is 10,369,280.19 for the baseline scenario. We increased the trust level by 10% in each level and we looked at the carbon reduction as a result of these changes. You can see in the first line of the graph, which is associated with the network of 1000 firms, by changing the trust level for 10% percent of each level we have the average increase of 11,388,286.83. This increasing trend is more impressive when the number of firm increase in the network either. In the network with 1500 firm, the average increase of the carbon reduction is 2,503,631.23 and when firms number in the network gets 2000, the average increase in carbon reduction is 4,398,683.80.

After all of this analysis for the trust, we suggest some ways to improve the trust level in an industrial network. Trust in an IS network can grow by increasing relationship or having workshops with a related subject that in this way managers become familiar with the advantages of building trust (Cavalcanti et al., 2017). It is also mentioned that having a direct and face to face relationship can help to build trust between buyer and supplier (Ketkar, Kock, Parente, & Verville, 2012).

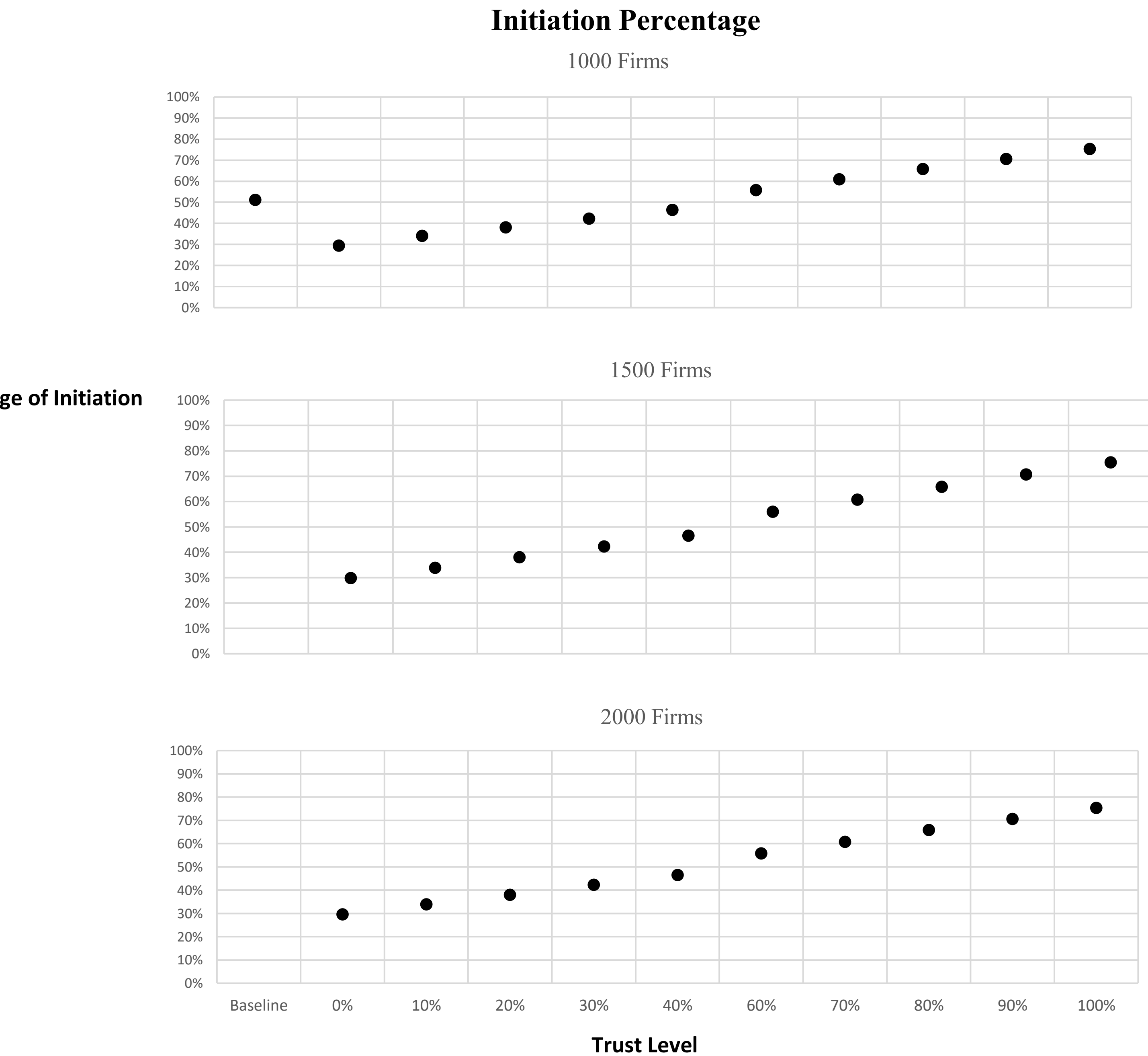


Figure 35: potential Initiation and Completion percentage as a result of increasing Trust level in the network

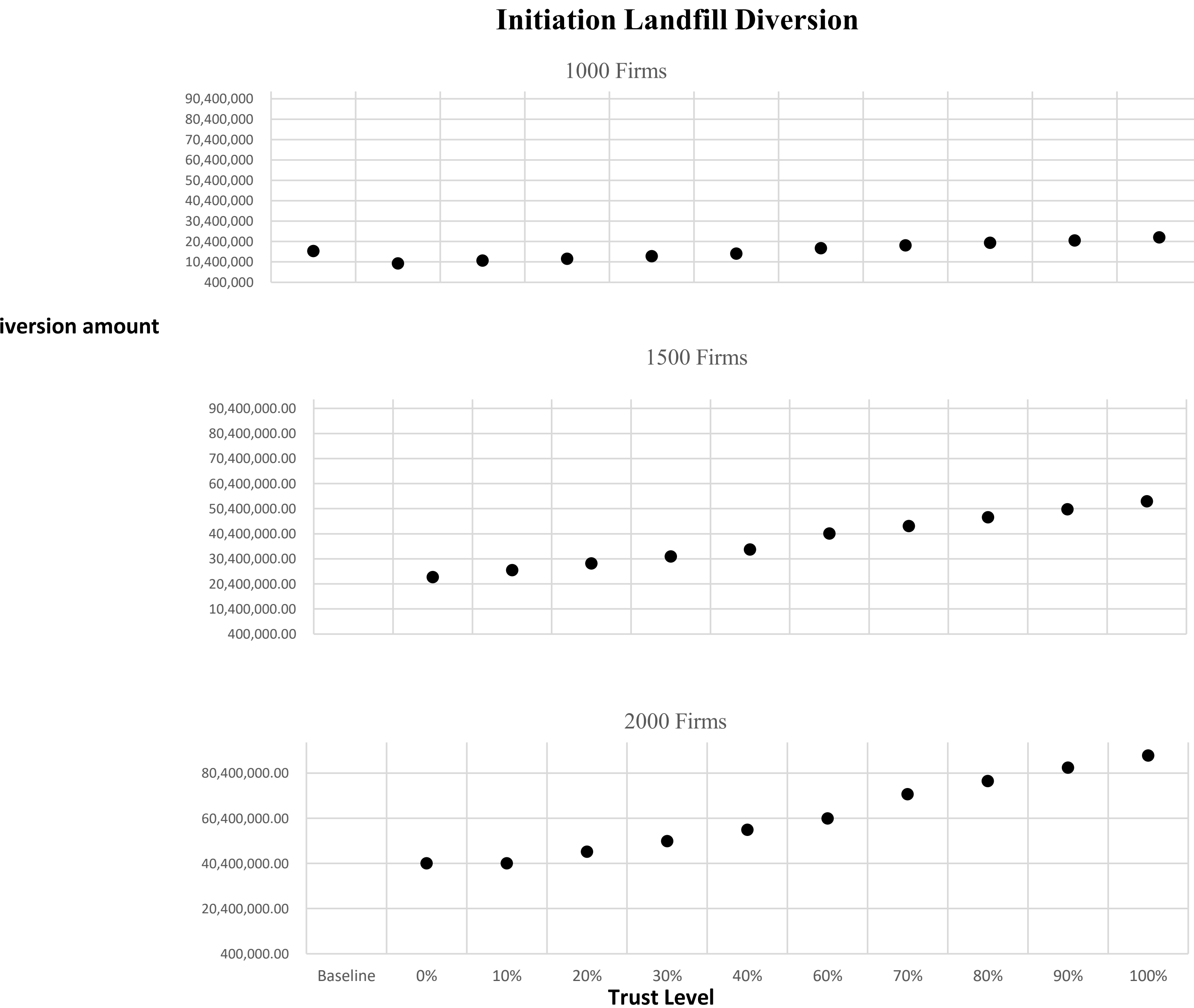


Figure 36: Potential landfill diversion changes as a result of increasing Trust level in the network

Table 27: Increasing of carbon reduction in detail as a result of increasing Trust level in the network

looking at the increasing of carbon reduction in detail by increasing initiation				
increasing of trust	Firm numbers in the network	Real Carbon Reduction	increasing of each level from its previous level	Average increase
Baseline	1,000	10,369,280.19		
0.00		5,821,428.04		
0.10		6,803,735.33	982,307.29	1,056,450.17
0.20		7,661,030.51	857,295.18	
0.30		8,487,162.57	826,132.06	
0.40		9,310,767.62	823,605.05	
0.60		11,388,286.83	2,077,519.21	
0.70		12,369,113.11	980,826.28	
0.80		13,295,470.66	926,357.55	
0.90		14,295,562.67	1,000,092.01	
1.00		15,329,479.53	1,033,916.87	
0.00	1,500	14,004,423.56		
0.10		15,960,511.54	1,956,087.98	2,503,631.23
0.20		17,987,767.60	2,027,256.06	
0.30		20,165,155.30	2,177,387.70	
0.40		22,197,652.23	2,032,496.93	
0.60		26,753,790.11	4,556,137.88	
0.70		28,983,301.70	2,229,511.59	
0.80		31,705,966.08	2,722,664.38	
0.90		33,997,881.28	2,291,915.19	
1.00		36,537,104.60	2,539,223.32	
0.00	2,000	24,492,743.06		
0.10		28,142,899.11	3,650,156.05	4,398,683.80
0.20		31,756,991.02	3,614,091.91	
0.30		35,541,619.67	3,784,628.65	
0.40		39,124,974.85	3,583,355.18	
0.60		47,083,715.79	7,958,740.94	
0.70		51,071,913.87	3,988,198.08	
0.80		55,772,199.41	4,700,285.53	
0.90		59,607,421.91	3,835,222.51	
1.00		64,080,897.28	4,473,475.36	

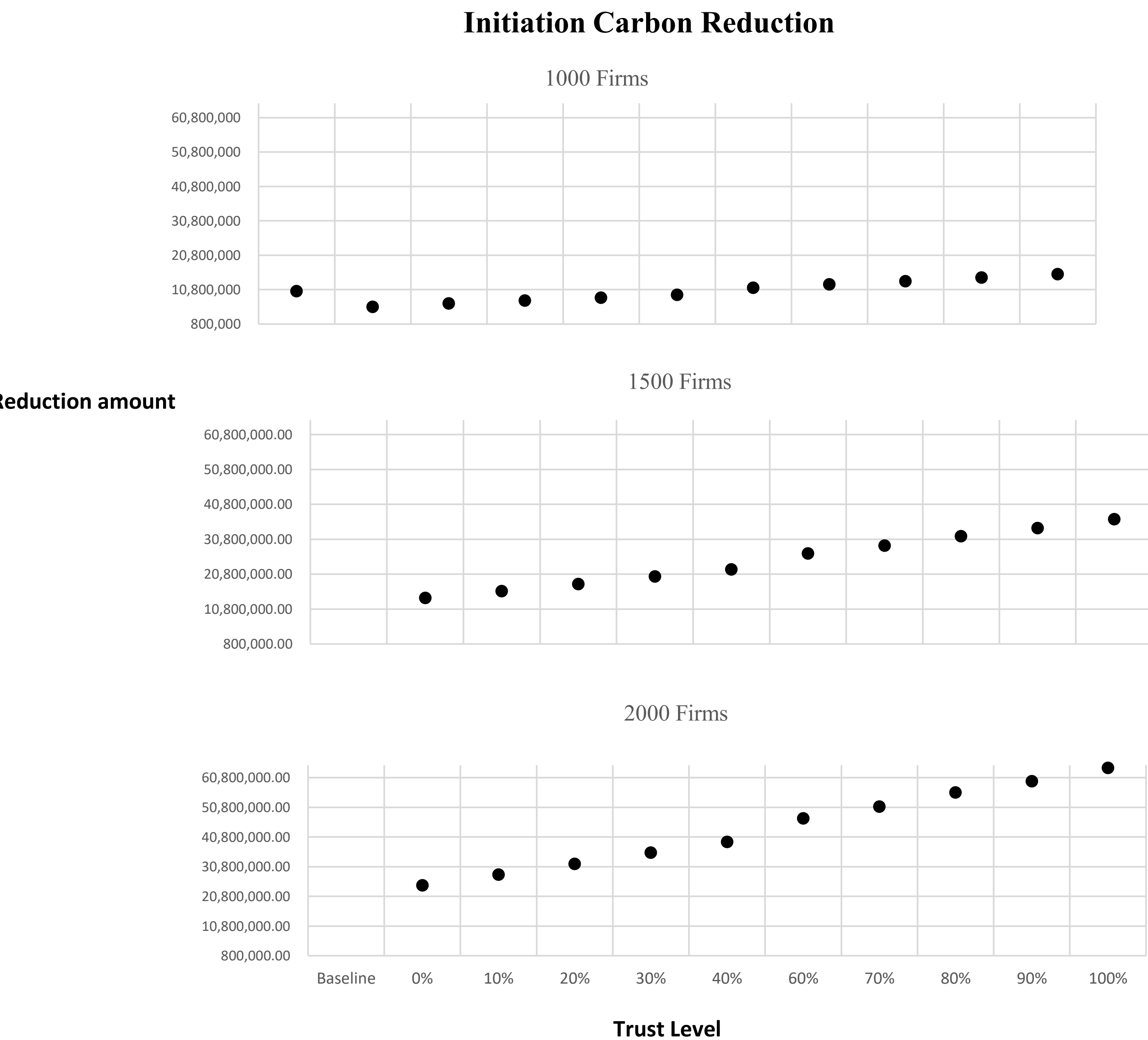


Figure 37: Potential Carbon reduction changes as a result of increasing Trust level in the network

7 Conclusion:

The logistic regression model gives us the significant factors, so we can find some of the most influential parameters for making the firms enter the network and continue synergy. Distance to NISP, Waste Quantity, Landfill Diversion, CO_2, Cost Savings and, Distance between two firms are the factors that play important roles and convince firms to come to the network and also some of them influence them to complete in the network.

After finding the significant parameters and structuring the model from the network, we saw that increasing the number of firms in the network resulted in an increase in either the amount of landfill diversion or the amount of carbon reduction. Thus, to find good policies to make a growth in the number of firms through the network, we analyze several hypothesis.

Looking to the result of sensitivity analysis suggests that having variation in different parameters such as landfill and carbon tax, the distance between two firms, distance to NISP and, the age of waste creates positive influences on the IS network outputs. For example, the completion percentage will increase by decreasing the age of wastes. The initiation percentage will increase by increasing landfill tax, and carbon tax. More distance between two firms and distance to NISP also positively affected the network by increasing the initiation percentage. Having less distance between two firms also helps to increase the completion percentage. Increasing the completion percentage helps to create a more sustainable environment since more firms will be reluctant to leave the network after joining it and then also incline to cooperate by presenting additional wastes into the network. This is a positive result; however, we need to consider something that motivates more firms to initiate in the network and start doing synergy. This is because when the number of initiated firms gets higher, more firms have the chance of completion in the network because completion only happens within the pool of initiated firms. Therefore, we need to find a way to increase initiation and in this regard, we evaluate trust in the network. In other words, the hypothesis is what would happen if the trust increase or decrease in the network. The reason for doing this is that if you look at the result of the distance you can see that the higher the distance the higher the rate of initiation. Thus, the level of trust could be the reason for that. If we increase the trust, firms could rely on each other when they are close. We check if a manager has more trust in others does it motivate her/him to start synergy in IS network?

Based on the results for trust analysis, it appears that adding trust to the network not only increases the initiation percentage but also helps firms to continue to participate in the network, thereby strengthening industrial symbiosis and environmental sustainability. The level of trust is important in an industrial symbiosis network since there are a variety of streams for material, energy, etc. and each stream includes different flows between firms, which is synergy between firms, so having a low level of trust makes all of the potential flows to stuck (Gibbs, 2003). Our results demonstrate that both landfill diversion and carbon reduction are increasing as a result of increasing trust in the network. At the same time, you could see that decreasing trust effect on initiation significantly while it does not influence on completion a lot. It demonstrates that while two pairs started synergy together the trust is already between them and there are a few of them that lose the trust after reaching it. This improvement shows that we really need to work on trust level more than anything in our network. Increasing trust in the network is therefore essential to increase the level of participation in IS networks, and in the level of materials exchanged and diverted. Public policy can play a key role in improving the level of trust level in networks by providing better interpretation from "economic geography and regional economics" point of view for network expansion (Gibbs, 2003). The government can also help to further development of the network by providing more funds in these fields that researchers can analyze the regulations and economic incentives through the network (Gibbs, 2003). Cavalcanti et al. believe that the trust will grow by increasing the relationship between firms, they assert that the actions such as workshops with the related titles to trust can shape trust between firms(Cavalcanti et al., 2017). Ketkar et al. also asserts that having direct relations can increase the trust between buyer and supplier (Ketkar et al., 2012) Based on what we have done so far I want to prioritize the different policies that the government can apply to have a better output from the IS network. Table 28 demonstrate the policy priority:

Table 28: The priority of the different policies

priority	policies	Advantage
1	Increasing trust in the network	1. Increasing either the number of the firms which come to the network or those that continue synergy or add additional wastes to the network 2. Increasing the amount of landfill diversion and carbon reduction
2	increasing Carbon tax	Increasing the initiation percentage. Carbon reduction and, landfill diversion increases in both stages.
3	increasing landfill tax	Increasing the initiation percentage, landfill diversion and carbon reduction in this stage.

4	Applying IS in a big city	Increasing the initiation and also landfill diversion and carbon reduction in initiation stage.
5	Applying IS in a small city	Increasing the completion and also landfill diversion and carbon reduction in completion stage.
6	Find a match as soon as possible to use a less aged waste in the network	Increasing the completion and also landfill diversion and carbon reduction in completion stage.

8 Future Work:

For the future work, I would suggest considering a smarter function as the decision function of the model since a smarter function would help to consider a package of incentives. Considering this situation was not possible in our function.

Another thing is considering pairs with more firms instead of sticking with two firms in each par. This is beneficial because in the reality there would be firms that buy/sell their wastes from/to several firms; thus, considering it helps to be more close to the reality.

For the trust section, the assumption of our model is that there is a pool of firms that NISP facilitator already found them and also discovered potential matches for them. Our limitation in this regard was that we do not have enough data about facilitators and firms. Most of the characteristics that we have in our data are about firms in pairs; therefore, we build our model based on the pairs. In our model, we tried to increase the number of firms acceptance to start synergy and complete their synergy by adding more waste to the IS network. One of our hypothesis was increasing the trust causes firms to have more intention to start and complete in the network. In the future work, we suggest considering trust between NISP facilitators and firms in the prior stages as well.

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