IRIS Utrecht presenteert:

Smart-city entrepreneurship – the role of business incubation for kick-starting the urban transition

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Achtergrond/context van het rapport of product:
Because of urbanization and the pressure on the quality of life in cities that comes with it, it is relevant to know how smart city initiatives can be encouraged. This thesis looks at smart city startups and their performance in comparison to non-smart city startups after being incubated.

Kernvraag:
What is the effect of smart city start-ups on performance measures such as survival and size within the Utrecht Incubator?

Samenvatting:
This paper is about dismantling the effect of smart and technological start-ups towards performance measures such as survival and size. We have compared "smart-city start-ups" and "non-smart-city start-ups" within the incubator of Utrecht. Former research has indicated contradictive findings in this field of study, which is still relatively unexplored. Performance has been measured with the two different independent variables and by using a logistic as well as a negative binomial regression. These quantitative results have been aligned to the qualitative insights we have gained by conducting several interviews, which focused on personal experiences regards online incubation. The analysis has revealed a significant positive effect of smart city start-ups and the smart city score towards the success rate of incubated start-ups. Furthermore, the implemented control variables were discovered to have substantial correlations, which matched prior studies. The obtained results will help not only incubator programs but also aspiring entrepreneurs to critically reflect on decisive factors to kick-start the urban transition.

Tags:
Start-up performance; smart city; technology

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Smart-city entrepreneurship – the role of business incubation for kick-starting the urban transition

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Abstract

This paper is about dismantling the effect of smart and technological start-ups towards performance measures such as survival and size. We have compared "smart-city start-ups" and "non-smart-city start-ups" within the incubator of Utrecht. Former research has indicated contradictive findings in this field of study, which is still relatively unexplored. Performance has been measured with the two different independent variables and by using a logistic as well as a negative binomial regression. These quantitative results have been aligned to the qualitative insights we have gained by conducting several interviews, which focused on personal experiences regards online incubation. The analysis has revealed a significant positive effect of *smart city start-ups* and the *smart city score* towards the success rate of incubated start-ups. Furthermore, the implemented control variables were discovered to have substantial correlations, which matched prior studies. The obtained results will help not only incubator programs but also aspiring entrepreneurs to critically reflect on decisive factors to kick-start the urban transition.

Key words: smart city, start-ups, performance, business incubation (online, offline)

JEL codes: C13, L25, L26, M13

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Table of content

1. Introduction

The city of the future requires entrepreneurship with a wide range of complex and diversified business models. Therefore, the question arises how incubation is altering the appearance of such smart-city entrepreneurship, especially within COVID and the necessity to adapt from offline to online incubation and why it is comparatively difficult to create these ventures in smart cities. Ideas within the sector of smart city entrepreneurship will become essential in the upcoming years, not only to become technologically leading but also to implement a sustainable urban planning since more than 50% of the world's population are living in cities with a continuous growth (Ritchie, 2018) and consequently causing enormous challenges for our societies. The more people, the more traffic, the more pollution, the more energy consumption, the more water usage, and the more waste are the unpleasant consequences. Smart cities have been increasingly gaining attention to help coping with these occurring and vital problems (Almirall et al, 2016). Although, as we strive to become smarter, the reality can be quite different, currently being depicted by the Covid-19 crisis and a new trend of urban exodus. Supposedly, humanity tends to fall back into old structures and cities will continue to grow, when the crisis is turning towards its end (Lima et al., 2020). The effects will be or already are the struggling city infrastructure trying to keep up with the demand. Associated air quality grievances causing 500,000 premature deaths a year, multiplying heat waves because of climate change and the missing right of codetermination within a broader segment of society are ongoing trends within Europe (European Commission, 2020, Naumann et al., 2020).

The Smart City idea has drawn interest in the EU in recent years, with numerous schemes set up in the countries. Programs, such as Horizon 2020 have set targets directly connected to the creation and growth of smart cities in European countries (Almirall et al., 2016). The consortium members are actively working on the following challenge during the IRIS Horizon 2020 demonstration project. IRIS is a collective of cities working to bridge the addressed gap by combining social, digital, and technical innovations to improve the urban environments for all citizens and our planet. The organization is trying to tackle several key areas of transition by externalizing their solutions and results to inspire other European cities to become smarter, cleaner, and healthier (IRIS, 2017).

After illuminating the importance of smart cities, the question arises how business incubators can originate smart-city start-ups. Research has demonstrated a correlation between smart city and incubation. As both terminologies comprise "innovation" within their central theme, it becomes vital to collaborate on creating and funding innovative activities to enhance the development of their urban surroundings (Blanck et al., 2019). Becoming a smart and technological city has to align with the existent incubation ecosystem from a practical point of view.

Incubation is not about delivering a variety of general business tools or taking the start-up by the side and showing the way ahead (Eveleens, 2019; Alvarez and Barney, 2007; Dimov, 2018). It is rather alleviating start-ups from any conceptual prejudices through a personalized and diverse combination of resources. This incubation encourages a creative learning environment that is crucial to disruptive entrepreneurship and can substantially affect start-up success (Eveleens, 2019). Since incubation have a beneficial impact on start-up results, it would be valuable to better clarify how incubation comes into being and is affected as a dependent variable. Consequently, discussions can be elaborated on a wider aggregated scale of analysis (Eveleens, 2019) by examining geographic impacts of incubation on well-being and productivity or comparing performance of incubated start-ups with non-incubated (Nijland, 2020) to gain a better general understanding of the concepts and thus pursuing research.

Academic relevance has been substantiated by IRIS and several other organizations within the EU. It will be crucial to further investigate it, given that the terminology of smart-city entrepreneurship, especially in combination with business incubations, is novel in the field of entrepreneurial literature. Incubated firms are considered one of the main drivers of job creation and innovation (Eveleens, 2019). Furthermore, Eveleens (2019) stated that relevant literature within that field changed from single surveys and interviews with only incubated start-up entrepreneurs to research going hand in hand with practical implementations and thus indicating strong dynamics and scope for potential continuations in the future. Baraldi and Ingemansson Havenvid (2016) are lastly emphasizing the better understanding of incubators to obtain a great benefit for entire ecosystems in Europe and throughout the world.

Our research is creating social impact and direct recommendations for policy makers, urban planners, or business incubation managers by supporting cities to solve their urgent problems. It will provide a better understanding of how business incubation can foster smart-city start-ups. The evaluating performance of the collected start-ups needs to further investigate business incubators, which should create value by combining the start-ups' entrepreneurial drive with the necessary resources. Thus, the following research question was formulated: *What is the* *effect of smart city start-ups on performance measures such as survival and size within the Utrecht Incubator?*

Therefore, the study is based upon the existing literature of smart-city entrepreneurship and will further elaborate on it by dismantling the term of smart-city, linking business incubation to innovative city projects. After illuminating the theoretical framework, it will be elementary to discuss the quantitative data by using an index (SCI) and ultimately compare them with the qualitative analysis within a mixed methods research design of incubated start-ups and their distinction towards physical (offline) and digital (online) incubation. Are smarter start-ups more likeable to survive and did the pandemic increase digitization of incubators and thus allowed better assistance of multiple incubated start-ups?

2. Theoretical Framework

2.1 Smart city

Even though smart cities have a growing interest within research, it is impossible to universally define the phenomenon as the subject is as widespread as diverse (Almirall et al., 2016). The same meaning is falling under different terminologies as innovative city, knowledge city, digital city or intelligent city (Tan, 1999; Krisna Adiyarta, 2020; Sun & Poole, 2010; Ismagilova et al., 2019; Barth et al., 2017; Sproull & Patterson, 2004; Sussman, 2001). These far-reaching interpretations are helping us better understand the concept and confusing since they are impeding the generalization, comparability, and relevance of the presented concepts for scientific studies.

“A city is smart when investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and high quality of life, with a wise management of natural resources, through participatory governance” is nonetheless used repeatedly as a quote (Caragliu, Del Bo & Nijkamp, 2011, p.70). Most academics stress the quality of life, the well-being of people, technology, or government. But other subjects, such as creativity, cooperation, and technology, are often combined.

The notion that a smart city contradicts the old way of doing it in the built world is what both concepts appear to have in common. It emphasizes entrepreneurs (Lombardi et al., 2012). However, it is much harder to describe a smart city start-up when there is no easily accessible smart city concept. Therefore, the methodological literature on start-ups in smart cities is limited to date (REFS).

Governments are acting now as data facilitators for entrepreneurs and start-ups. The more data is accessible, the better public services will be established. New digital solutions are on the rise to create an improving comms-based sharing economy focusing on generated data and gathered by citizens, Internet of things (IoT), sensor networks, and open city level data to establish a broad communal use without violating personal laws. In smart cities it is easy to do the right thing by feeling supported to act sustainable. For instance, to use public transport instead of your car, sharing instead of owning things or economizing on resources rather than wasting resources. Data can be essential for a smart city to design intelligent applications for the city and its residents (Almirall et al., 2016). Caragliu & Del Bo (2019) discovered that smart-city policies have a significant positive effect on urban innovation as measured by patenting activity, especially in high-tech fields via PSM (Propensity Score Matching), which creates an artificial control group by comparing each treated unit with a non-treated unit and identical characteristics using statistical techniques.

This discrepancy between ideology and actual implementation of the smart city idea suggests that technology is not only a tool for enhancing urban conditions, but that its use is now publicly recognized as having strategic significance in achieving political consensus (Nilssen, 2019). The author created a smart-city continuum with four dimensions, ranging from a technology-focused dimension to corporate and collective innovation-focused dimensions to a more inclusive experimental dimension. A practical case is substantiating the importance of a "multifaced urban innovation". Although all these four aspects are crucial for the current state of urban planning, it comes down to the willingness of governances or the establishment of urban incubators to allow cities to flourish.

2.2 Business Incubation

Business incubation is the decisive force to accelerate such flourishing progress. It characterizes by a support to start ventures while providing access to services and resources (Eveleens et al., 2017). More than 7000 incubators have evolved over the last five decades. The history of incubators is indicating that the first generation concentrated on a well working infrastructure, whereas the second already delved into one-on-one business advice. Modern incubators aim to provide facilitating networks. Because of that start-ups have access to intangible resources such as knowledge and legitimacy. These are specifically important for ambitious entrepreneurs

(Eveleens et al., 2017). Innovation in the design of a "smart city" is a valuable technique. Via the implementation of new technologies, start-ups build demand and are an important vehicle for innovation (Eveleens, 2019; Mason & Brown, 2013). Business incubation is a widespread method of support for start-up firms. What are thus the impacts of business incubation on start-ups?

2.3 Incubators impelling smart-city start-ups

The research gap must be elaborated and embedded into the empirical strategy of the thesis with an emphasis on both concepts of smart-cities and business incubation. Different research on business incubation effects on performance reveals disagreement with outcomes (Colombo & Delmastro, 2002; Dvoulety et al., 2018; Eveleens, 2019; Löfsten, 2010; Löfsten & Lindelöf, 2002; Westhead & Storey, 1997). Performance is difficult to grasp because of its open interpretation (Eveleens, 2019; Lukes, Longo & Zouhar, 2019). Much analysis thus requires the use of a variety of interventions (Wiklund & Shepherd, 2003). Incubated businesses, however, are seen as one of the prime generators of job growth and creativity.

Since the Utrecht Inc. focuses on tech start-ups, it becomes apparent that smart city start-ups should be favored within the selection process. Nonetheless, research has shown a negative correlation between business incubation and survival rates of these start-ups (Lukeš et al., 2019; Madaleno et al., 2018). Newly established technological ventures require a longer initial phase to reach market maturity because of their ground-breaking innovation (Lukeš et al., 2019) As smart city start-ups are defined as such technological ventures, the question arises if their survival rates are comparatively lower and their development will be subsequent (Ferguson and Olofsson, 2004).

A particular focus lies on technology having the ability to significantly impact climate performance and provide a competitive advantage for its business result, thus creating a paradox. The so-called start-up paradox is unique to the context (Leendertse et al., 2020). By concentrating on novel and hardware technology, start-ups will partially avoid this paradox, emphasising investments. Since investing in such sustainable start-ups not only characterises you as a change agent but also adds societal value to your actions. Therefore, these investments are helping start-ups to escape the “vicious cycle”. Incubators though, can understand the importance of software and hardware-based start-ups to align their investment with societal or profitable goals. The idea of “green growth”, especially in smart cities seems not for nothing the challenging question of our time (Leendertse et al., 2020).

As stated before, it will be substantial to use quantitative and qualitative data to elaborate on different effects between incubation assistance before and after the pandemic. Are we able to see an increasing number of incubated start-ups within the field of smart cities because digital support allowed incubators to advise a larger field of new ventures?

When evaluating the success of incubation, most of the research has focused on the characteristics of the incubator. However, there has been less research conducted on the features of incubated start-ups. Furthermore, less study has been undertaken in the field of "smart city start-ups”. We are hoping to close this research gap with our paper's outcomes and provide indications for cities to become smarter and thus more sustainable. Problematic is the various research on the impact of business incubation towards performance because of its contradictory findings. Performance is a broad and imprecise concept and thus hard to measure (Eveleens, 2019). We tried to test the following hypotheses by applying two of the control variables *entrepreneurial experience* and *age* towards survival and growth factors.

H1: Smart city start-ups are more likely to survive than non-smart city start-ups

H2: More entrepreneurial experienced founders are establishing smart city start-ups

H3: The age of the start-up is influencing the performance measures of survival and growth

2.4 Digital Transformation of Incubators

Van Rijnsoever (2020) has highlighted the role of incubators as intermediaries to overcome weak network problems in modern entrepreneurial ecosystems. The author developed a theoretical model in which network development functions as “meeting” and “mating” in an incubator setting and applied the insights gained to an agent-based model, which allowed for estimating how each support mechanism contributed to overcoming weak network links in a financial support network. The conclusion was that the systematic benefits of incubators also greatly enhance their societal value proposition. Klofsten et al. (2020) emphasized the incubator size and specialization issues and demonstrated that size is important in achieving efficiency and networking benefits for clients. Incubators can play an important coordinating role in the formation of technology networks with diverse actors, such as researchers, scientists, technological students, sciences and engineering, managers, policymakers and entrepreneurs.

It is thereby vital to elaborate on the current dynamics of incubation. The COVID-19 pandemic changed the operations of incubations programs dramatically. Especially smart city start-ups in their early stages are heavily depending on the support of incubators. The question arises if these ventures profited from the latest developments. On the other side, we must illuminate the execution practices of incubators. Did the adaption lead to a reduced number of incubated start-ups? Did it even enhance the support of single ventures since the endorsement is more direct and sophisticated? Qualitative data collection in combination with our quantitative results will help us to tackle these underlying assumptions.

H4: The transformation from offline to online incubation improved the performance of start-ups and thus the survival rate

3. Empirical Strategy

In this section, we will explain how data was gathered and processed to address the research question. Incubation programs in Utrecht and interviews with entrepreneurs of those provided the data. We have decided to use a mixed methods research design since business incubation depicts a complicated process. The evaluation of the data sheet with the topicality of the pandemic needs to be combined.

3.1 Research design and data collection

The data of the start-ups in Utrecht was collected at Utrecht Inc. with the help of the IRIS smart city project. UtrechtInc was founded in 2009 to provide an open working environment where companies can grow. UtrechtInc is ranked in the top 10 university business incubators globally by the UBI World Incubator Raking in 2019. (Meyer & Sowah, 2019). It has links to Utrecht's information institutions, such as Utrecht University (UtrechtInc, n.d.). The dataset consists of information about their actual existence, smart-city categorization, and number of employees. Financial information such as revenue has been difficult to scrape. The data sheet has been complemented with more information gathered by web search (browsing, LinkedIn). The companies and mostly the founders, the founding year and if the start-up survived, were looked up on LinkedIn. Furthermore, LinkedIn displayed a specific year the start-up stopped operating. Information about the employees has been additionally gathered via LinkedIn as well as their company's websites. Lastly, we reached out to the ventures via their official e-mail address and asked about the number of employees they are employing at the time of data collection.

The sample contains 168 start-ups and depicts applications from the beginning of 2017 till September 2020. This dataset covers both approved and unselected start-ups for the incubation scheme. These start-ups were left out of this study because it focuses only on incubated start-ups.

Table 1: Overview of data collection sources

Data	Variable	Sources
Start-up success	Survival	LinkedIn, company website, Facebook, Crunchbase
	Size	Company website, LinkedIn

3.2 Variables

The variables, which used in the study are discussed in this section. An overview can be found in Table 10 (see Appendix A) with the dependent, independent and control variables.

The dependent variables must be diverse to test start-up performance sufficiently. *Survival* as a binary variable is used to measure if the ventures are still active when we have collected the data. To enhance the measure's dependability, it was gathered from a variety of sources. The survival variables were coded via the website, LinkedIn and web search. Start-ups, which have changed their name or acquired by another company, were also defined as a survived start-up. The second dependent variable is the *size* of the company, indicating the number of employees via a count variable at the time of data collection. A non-survived company sets the variable to zero. The data was scraped via LinkedIn and web search, and as earlier mentioned contacting the companies via e-mail. At first, we wanted to distinguish performance between financial and non-financial indicators. Such a financial variable would be the amount of investment. Still, a vast majority of the companies did not display such information and thus we decided to exclude it from the analysis.

The independent variables being used relate to "smart-city start-up" and if the targeted companies can be classified as such. We have used two independent variables. Firstly, a *smart city* start-up is used as a binary variable and coded with 1 if the firm is a smart city, 0 if it is not or if the venture is not operating anymore. Companies, which did not survive, have been also coded with 0. We have used the coding scheme of the SCI ((Hermse et al., 2020), see table 3). Secondly, the categorial variable *smart city score* is differing from 0-6 where 0 and 1 complies with the *smart city* binary variable and 2 to 6 are in contrast intensity factors, stating the higher the figure is, the more smart-city characteristics are being fulfilled by the start-up (Hermse et al., 2020).

Control variables are applied to the study to improve the quality of the data. The following six control variables will be applied to the model based on the literature and Eveleens (2019) and Leendertse (2018) analysis. Firstly, we have included the dummy variable online/offline to validate our hypotheses if recent data analysis of digital incubated start-ups has already impacted performance. The variable was coded with 0, if the start-up had offline incubation and 1 if it had online incubation. Secondly, entrepreneurial experience is added and used as a binary variable, coded with 1 if at least one founder has prior entrepreneurial experience, 0 if not or the company is no longer active. Thirdly, gender disparities in the founding team are considered, as evidence has shown that male-founded companies outperform female-founded businesses (Gottschalk & Niefert, 2013; Kalleberg & Leicht, 1991). The number of males in the original founding team was used to operationalize this measure. This variable's squared value is also used in the formula. The used ratio variable indicates that 0 equals only female founders, whereas 1 depicts only male founders. A decimal of 0.5 thus shows that 50% of the founding team are male. Fourthly, the founding team's scale is used as a control variable with a count measurement. According to the findings, team size and start-up success have a strong correlation. More creative ideas to be produced as larger teams can more efficiently mobilize capital and a greater variance in expertise (Jin et al., 2017; Klepper, 2001; Leonard & Sensiper, 1990; Soetanto & Jack, 2013). Another feature is the market type. The business climate and the type of industry have been shown to influence start-up success in the literature (Sandberg & Hofer, 1987; Song et al., 2008; Wright & Stigliani, 2012). A dummy variable is used to add this discrepancy. Lastly, we have factored the age of the company into the model. The age of the start-up and its performance have a substantial favorable link (Soetanto & Jack, 2013; Song et al., 2008). The count variable is measured in months and 0 signifies that the necessary information of the start-up was not discoverable.

3.3 Descriptive statistics and Smart-City Index (SCI)

The sample included 168 start-ups for which all necessary information was available. Table 2 is depicting the number of observations, the mean, standard deviation, and range for each variable we were using. *Survival* as our first dependent variable depicts that 93 out of 168 start-ups survived, which equals a percentage survival rate of 55.4%. The second variable *size* indicates that the average number of employees within our data sheet is about 4 people. Out of the 168 observed start-ups, we can conclude that less than a quarter of them are categorized as smart city start-ups. Only 21% of one of the founders have entrepreneurial experience. The standard deviation is higher, probably because of the high number of zeros in the data sample. The average number of founders is close to 2, which substantiates that it appears to be easier to establish a company with another person.

Furthermore, the variable *gender* was heavily skewed towards a percentage of male founders (83%), which signifies a small number of women in the dataset. It was also striking that they mostly founded start-ups by themselves. The average age of the start-ups in the data sheet, either still active or not was about 19 months. Lastly, in 32% of the cases, the start-up is a market B2C.

Table 2: Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Survival	168	0.554	0.497	0	1
Size	168	1.875	3.163	0	15
Smart city start-up	168	0.214	0.411	0	1
Smart city score	168	1	1.741	0	6
Online/Offline	168	0.512	0.501	0	1
Entrepreneurial Experience	168	0.208	0.407	0	1
Founding team	168	1.827	0.841	1	5
Gender	167	0.835	0.313	0	1
Market type	157	0.325	0.470	0	1
Age start-up	168	19.351	28.791	0	216

SCI is a numerical technique for coding „smart city start-ups" based on the number of times, keywords appeared in smart city concepts. It comprises of two requisite conditions and five intensity conditions. A company is accepted as a smart-city if it has met at least the requisite criteria. Requisite criteria are considered as a technological background of the company and tackling an „urban challenge“ („city“). Terms such as blockchain, digital infrastructure, AI and ICT are among those. Another concept, which is often used for this condition is „urban environment“. The start-up is coded with 1, if it applies to these. If that is not the case, it is coded with 0, a so-called „non-smart city start-up. The score on the scale of smart city start-ups can rise by meeting one of the intensity requirements, which are „citizen”, „environmental sustainability“, „ICT“, „quality of life“, „economic“. The ranking of the Smart City Index (SCI) is calculated using the formula below. Both intensity conditions are weighted equally.

$$SCI = (technology*city)*(1+ICT+citizen+environmental\ sustainability+quality\ of\ life+economic) \quad (1)$$

Table 3 shows absolute numbers as well as percentages for each city and topic. “City” (City), “Technology” (Tech), “Quality of life” (Qual of Life), “Citizen” (Citiz), “Sustainability” (Sust), “ICT” (ICT), and “Economic” (Economic) are the topics (Econ). Because the sample exclusively includes technology-based companies, the proportion of “Technology” should always be 100%. It's worth noting that when "ICT" is coded one, "Technology" is likewise coded one - not the other way around. Furthermore, the term "citizen" may only be coded if the word "city" was used.

Table 3: Results of smart city coding

			City	Technology	Quality of Life	Citizen	Sustainability	ICT	Economy
Utrecht	90	#	35	89	66	40	27	60	34
		%	38.89%	98.89%	73.33%	44.44%	30.00%	66.67%	37.78%
			0	**1**	**2**	**3**	**4**	**5**	**6**
Smart city start-up	90	#	54	0	1	7	9	10	9
		%	60.00%	0%	1.11%	7.78%	10.00%	11.11%	10.00%

The table indicates that most start-ups from Utrecht are tech-based since the incubator has focused on technologically based ventures. Furthermore, health-related concerns (“Quality of Life”) are playing an ongoing importance, especially for founders within the Utrecht Inc. Surprisingly the coding revealed that only 30% of the 90 coded start-ups are addressing sustainable matters. Besides that, the distribution of the start-ups is extreme. Ventures are either no smart-cities (60%) or show various characteristics of innovativeness (31%).

We will use this method to code the datasets for the Utrecht Inc. sheet. A cleaned text describing the start-up will be used to code. These descriptions have been scraped from the websites of the start-ups. When the information was insufficient, we have used the description from LinkedIn. A significant number of start-ups did not have any description, which made it impossible to code them on the SCI and thus they had to be excluded from the coding analysis. Furthermore, the coding was done by two people independently to improve the reliability of the data. Following that, some erroneous findings will be discussed and corrected as needed.

3.4 Data analysis

The cross-sectional data will allow us to use different regression models. I used Stata to regress several models to assess the link between the dependent and independent variables in this study (StataCorp, 2013). The independent variable *survival* is a binary variable. Therefore, a Binary Logit Model (BLM) is an appropriate regression with an addition of a penalized maximum likelihood logistic regression to test for the independent variable *smart city start-up*.

Because our second independent variable *size* is *a* count variable, we must either use a Poisson or Negative Binomial model (Long, 1997). When a variable has only positive, nonnegative integer values, it is termed (Hilbe, 2014). An alternative model is used because employing OLS can lead to biased findings in this scenario (Coxe, West, & Aiken, 2009). To verify if Poisson is a good fit, we are comparing the relative value of the variance to the mean after accounting for the effect of the predictors or checking for overdispersion. Following the descriptive statistics analysis, the variable *size* has a higher variance than mean (Table 4) and the Pearson Chi2 dispersion statistic is higher than one (Table 5), which indicates a preference for the negative binomial model. Additionally, we looked at the histogram of the dependent variable *size* (Figure 1) to identify overdispersion. The variable is skewed, which signifies overdispersion. Lastly, the goodness of fit of the Poisson has a p-value of 0.00 and demonstrates that the Poisson model is not a good fit. The missing number of zeros in the data set does exclude zero-inflated models as well. Because of these tests and assumptions, it was clear to use a negative binomial model to regress for *size*.

Both tests (logistic and negative binomial) have been segmented into three different models. Firstly, only with controls, then with the first independent variable *smart city start-up* and lastly with the second independent variable *smart city score*. Both independent variables are strongly correlated to each other and thus the results would be imprecise (see table 6 correlation matrix). We employ a McFadden pseudo-R-squared test to evaluate the models' individual performance. A good model achieves a score of between 0.2 and 0.4. (McFadden, 1973). Following that, we run a LR-test to determine the likelihood ratio of the models in contrast to the previous models.

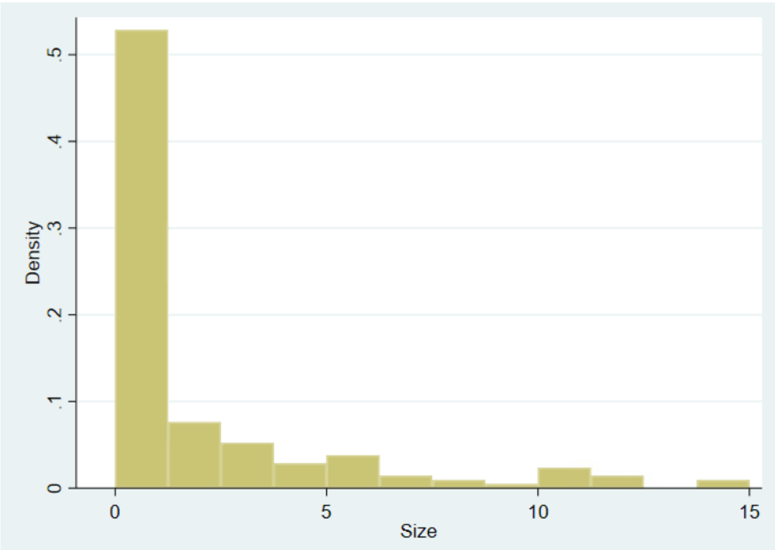
*Table 4: Detailed descriptive statistics of **size** (number of employees)*

	Mean	**Std. Dev.**	**Variance**	**Obs.**
Number of employees (*size*)	1.875	3.163	10.002	168

Table 5: Poisson goodness of fit

	Chi²
Goodness of fit	568.326***

*Figure 1: Histogram of **size***



The likelihood-ratio test of alpha=0 is indicating that the dispersion parameter alpha is equal to zero. The high-test statistic (38.76) implies that the response variable is over-dispersed, and that the simpler Poisson distribution does not adequately represent it. We also looked at the elements that affect inflation variation (VIF). All the VIF scores were below 2, indicating that the model's multicollinearity is no longer an issue (Field, Miles & Field, 2012). The correlation matrix has furthermore shown a positive correlation of the age of the venture towards its size. Online incubation correlates negatively in other hands towards the number of employees.

All of the 168 companies within the dataset were tried to be coded but we only gathered data of 90 start-ups. These were applied to the SCI-index and its seven elements. After cross-checking the data, it is crucial to converge on an individual way of coding. A consistent smart-city coding will allow us to determine how many UtrechtInc ventures have been smart cities and if they performed better with an online or offline incubation. The variable of turnover or employees is helpful in this context. These are part of the IRIS smart city project (IRIS smart cities, n.d.). Web scraping or social media analysis (LinkedIn, Obi4Wan) additionally depict methods to obtain more information about the performances of the incubated or non-incubated start-ups via archival data, observations, and surveys.

Qualitatively, interviews were conducted with project managers from Utrecht Inc. as well as founders from the used data-sheet for a better comprehension of bias towards user-innovation. We conducted five semi-structured interviews to obtain a surprising finding, monitoring the pattern or learn from an extreme case. Three interviews were done in English through an internet video conference and were videotaped for transcribing reasons. To maintain the guarantee of secrecy, neither the interviewees nor the organizations where they work are named in this thesis. A semi-structured interview guide (see Appendix C) was created according to the proposed framework. Firstly, we asked about the ideation process of the start-up and which role the incubator played in the decision-making process. The second section illuminated the incubation process closer, directly followed by questions about the beginnings of the incubated start-up. Lastly, we obtained more information about the extrapolation of the venture and a potential solo attempt without the incubator. The guide was adjusted throughout the interviewing process.

The interviews in the qualitative section of the study allowed for a deeper understanding of the quantitative data and thus performing a mixed methods research design. They were subjected to a basic thematic analysis, which allowed recurring themes to emerge among the interviewees' words. The used “triangulation” will allow us to compare the results of one process with data from another method. As a result, we integrate in-depth knowledge with determining the degree and frequency of constructs (Polzin, Sanders & Stavlöt, 2018).

The findings of the paper might be useful for incubator owners and start-ups. Start-ups should look at the specific success metrics that the incubator excels at to see if they apply to their company. Aside from that, it is beneficial to incubator users. More information is provided on what success metrics their incubator excels at, or vice versa. This allows the incubator to make any required policy changes. Besides that, smart city start-ups are more likely to fail because of the higher costs. Their technological background and thus their specification is resulting in a longer initial period to grow. Incubators might prescind from including them into their incubation program.

Table 6: Correlation matrix

Variables	Survival	Size	Smart city start-up	Smart city score	Online/Offline	Entrepreneurial experience	Founding team	Gender	Market type	Age
Survival	1.000									
Size	0.511	1.000								
Smart city start-up	0.451	0.289	1.000							
Smart city score	0.469	0.264	0.900	1.000						
Online/Offline	0.007	-0.073	0.082	0.160	1.000					
Entrepreneurial experience	0.334	0.276	0.227	0.248	-0.135	1.000				
Founding team	-0.066	0.090	0.005	-0.001	-0.014	0.019	1.000			
Gender	-0.054	-0.042	0.019	0.030	-0.052	0.103	-0.194	1.000		
Market type	-0.011	-0.063	0.137	0.154	-0.042	0.029	-0.040	-0.085	1.000	
Age	0.384	0.311	0.010	0.104	-0.252	0.323	-0.125	0.083	-0.049	1.000

4. Results

4.1 Regression analysis

Table 7 demonstrates the results of our regression analyses. The models (1) and (4) are only including control variables. Instead, models (2) and (5) have been run with the independent variable *smart city start-up*, and models (3) and (6) with the second independent variable *smart city score*.

Table 7: Results of regression models

				Dependent variable			
		Survival				Size	
Var	Control (1)	Full (binary) (2)	Full (score) (3)		Control (4)	Full (binary) (5)	Full (score) (6)
Smart city		omitted				1.119*** 0.286	
SC score			1.142*** 0.358				0.292*** 0.078
Online/Offline	0.792* 0.417	0.510 0.463	0.335 0.476		0.172 0.281	0.021 0.268	-0.145 0.279
Entre Exp	1.420** 0.694	1.268* 0.736	1.302* 0.754		0.311 0.331	0.392 0.312	0.297 0.314
Founding team	`-0.137 0.230	-0.156 0.258	-0.134 0.261		0.209 0.186	0.236 0.183	0.218 0.184
Gender	-0.827 0.646	-1.179* 0.710	-1.190 0.724		-0.307 0.444	-0.514 0.421	-0.546 0.425
Market	0.010 0.418	-0.381 0.491	-0.388 0.505		-0.238 0.295	-0.436 0.286	-0.456 0.290
Age	0.065* 0.015	0.052*** 0.016	0.045** 0.016		0.037*** 0.009	0.032*** 0.008	0.032*** 0.008
Constant	-0.264 0.881	0.063 0.975	0.073 0.994		-0.534 0.651	-0.581 0.612	-0.473 0.612
Obs.	156	120	156		156	156	156
Log Likeli	-79.282	-64.469	-64.297		-268.326	-260.291	-260.676
Chi²	51.89***	37.12***	81.86***		31.14***	47.21***	46.44***
McFadden R²	0.2466	0.2235	0.389		0.055	0.083	0.082
LR-test			29.97***		238.66***	210.61***	216.29***
	Note: *p<0.10, **p<0.05, ***p<0.01						

The LR-test indicates that adding “smart city score” as an independent variable to the model, is substantially improving the model fit (1% level).

The fits of the *survival* models are statistically significant at the 1% level. The control variable *online* is statistically significant at a 10% level of the first regression model of control variables. This indicates a positive impact on the survival rate of start-ups within our data sheet without considering the characteristic of a smart city since the subsequent regressions with our independent variables and *online* have been insignificant. Nonetheless our second hypothesis that the digital transformation of incubators improved the survival rate of start-ups has been satisfied. Another interesting finding within our logistic regressions was the control variable *entrepreneurial experience*, which was significant at all three models (5% and 10% level). It demonstrates that our hypothesis was confirmed that more entrepreneurial experienced founders are establishing smart city start-ups. With a 10% level of significance, *gender* harms the survival within the full binary model of the logistic regression. The hypothesis that age has a significant effect on the survival rate of start-ups has been substantiated by the significant results of the control variable *age* in our regression (1% and 5% level) as predicted by previous research by Soetanto and Jack (2013) and Song et al (2008). The highest McFadden value for *survival* has been obtained by model (3), pointing to the model's best fit with the independent variable *smart city score*. Nonetheless all models have a McFadden value between 0.2 and 0.4 and thus constitute a good model fit (McFadden, 1973).

Surprisingly, the independent variable of model (2) is correlating with the dependent variable *survival*, which is why we have an omitted variable bias in the second model. Our correlation matrix (see table 6) is substantiating that effect. The coefficient is thus overestimated. We can recognize from the output analysis that *smart city start-up* predicts success perfectly (!=0). Because determining the coefficient and standard error for such a covariate in a regular logistic regression is theoretically impossible, Stata excluded the covariate, along with all of the predicted outcomes (36) from the model. Thus, the independent variable *smart city start-up* is predicting the dependent variable perfectly and/or is behaving linearly to it and creates a “complete” phenomenon.

We figured out a solution to overcome the (quasi) “complete” separation in our logistic regression model. To decrease bias in generalized linear models, Firth (1993) proposed modifying the score equations. In logistic regression, Heinze and Schemper (2002) proposed utilizing Firth's technique to address the problem of "separation", a situation in which maximum likelihood estimates trend to infinity (become inestimable). We were able to include our independent variable into the regression test. We obtained statistically significant results for the whole model (1 % level) and the variables *smart city start-up* (1% level) and *age* (1 % level) by obtaining the same number of observations as in the other models (156). Our binary variable *smart city start-up* and the control variable *age* have consequently positive effects towards the survival rate of a start-up.

Table 8: Penalized maximum likelihood logistic regression output

```
                                                 Number of obs     =        156
                                                 Wald chi2(7)      =      26.23
Penalized log likelihood = -55.838627            Prob > chi2       =     0.0005
```

Survival	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
SmartcityS~p	4.057799	1.454471	2.79	0.005	1.207089	6.908509
OnlineOffl~e	.455267	.444869	1.02	0.306	-.4166602	1.327194
Entreprene~e	1.140371	.6897047	1.65	0.098	-.2114258	2.492167
Foundingteam	-.1342007	.2467141	-0.54	0.586	-.6177514	.3493501
Gender	-1.082373	.6761826	-1.60	0.109	-2.407666	.2429209
Markettype	-.3497135	.4708898	-0.74	0.458	-1.272641	.5732136
Age	.0474033	.0155454	3.05	0.002	.0169348	.0778717
_cons	.0360539	.9297643	0.04	0.969	-1.786251	1.858358

All models of the negative binomial regression regarding *size* of the start-ups were statistically significant (1% level). The LR-test indicates that the first model has the best fit, which was only run with control variables (4). Besides we obtained some significant results for our coefficients, thus confirming our *survival* model towards the hypotheses we have made. The independent variable *smart city start-up* is significant at a 1% level. Smart city start-ups compared to “regular” start-ups are expected to have a rate 1.119 times greater size of employees, while holding the other variables constant in the model. The same applied for our second independent variable *smart city score*, which is likewise statistically significant at a 1% level and therefore has a positive impact on the size of start-ups as well. The other striking coefficient in our negative binomial regression was again the variable of *age*, which was statistically significant in all three models at 1% level.

Overall, the results of both regression models were promising although the variable of online incubation was expected to score more significant results. Nonetheless, these results might lead to fruitful discussions not only within research but additionally for incubators and other aspiring entrepreneurs as well. Such developments will be discussed in the last section.

4.2 Robust standard error check

We performed robust standard error regressions (Table 9) to verify the obtained results. It was not affecting the estimated values of the main dependent variables of both models *survival* and *size*. The *smart city score* and *online* of the first model stayed statistically significant and the *smart city start-up* and *smart city score* variable in the negative binomial model. There were some differences between the robust and the default standard errors, specifically at the control variables. *Entrepreneurial experience* for instance was not statistically significant anymore in the robust test of the logistic regression. *Gender* remained significant in the binary model of the logistic regression and turned from insignificance to significance at the full model (3). The same applies to the variable *age*. In the regression model of *size* in contrast, the *age* variable remained statistically significant. This is indicating a stronger effect of *age* towards the *size* rather than the *survival* of a start-up. After all, the tests were informative and provided us with confirmation of our hypotheses and underpinned their real effect.

Table 9: Robust standard error regression

				Dependent variable			
		Survival				**Size**	
Var	Control	Full (binary)	Full (score)		Control	Full (binary)	Full (score)
	(1)	(2)	(3)		(4)	(5)	(6)
Smart city		omitted				1.119***	
						0.255	
SC score			1.142**				0.292***
			0.364				0.069
Online/Offline	0.792*	0.510	0.335		0.172	0.021	-0.145
	0.481	0.545	0.574		0.250	0.227	0.236
Entre Exp	1.420	1.267	1.303		0.310	0.392	0.297
	0.896	1.009	1.057		0.316	0.343	0.344
Founding team	-0.137	-0.156	-0.140		0.209	0.236	0.218
	0.187	0.208	0.211		0.174	0.167	0.168
Gender	-0.827	-1.179*	-1.190*		-0.307	-0.514	-0.546
	0.551	0.630	0.629		0.317	0.347	0.355
Market	0.010	-0.381	-0.388		-0.238	-0.436*	-0.456
	0.380	0.453	0.486		0.269	0.256	0.264
Age	0.654	0.052	0.453		0.036***	0.032***	0.032***
	0.050	0.052	0.052		0.013	0.011	0.011
Constant	-0.264	0.063	0.073		-0.534	-0.581	-0.473
	0.968	1.002	1.032		0.587	0.528	0.540
Obs.	156	120	156		156	156	156
Log Likeli	-79.282	-64.469	-64.297		-268.326	-260.292	-260.676
Chi²	17.60***	11.90*	37.13***		23.58**	56.93***	56.26***
McFadden R²	0.247	0.223	0.389		0.055	0.083	0.082
	Note: *p<0.10, **p<0.05, ***p<0.01						

4.3 Qualitative analysis

The qualitative analysis has been embedded into the paper to underpin our quantitative findings, specifically focusing on the digital transformation of incubators. With guidance of (Dearnley, 2005) we have gathered useful information to enhance our understanding of online incubation. Both managers from Utrecht Inc. (see Appendix C 1; 2) have emphasized the importance of physical facilities, which contribute to an inspiring environment, where entrepreneurs can exchange their specific knowledge. They have furthermore elaborated on the community aspect of an incubator. Trainers, who are giving workshops within the building, have been encouraged to guide start-up teams and create a group dynamic within the different founders. Being solely present in these knowledge hubs is specifically important for younger founders since they are among like-minded people. Start-ups, which are openminded towards such an environment have been preferably selected for incubation at Utrecht Inc. (UI). This incubator has launched an online program called "startupme" before the pandemic has started. It drew attention to a plurality of start-ups. Such intensive courses will filter most of them over a short period since these intensive programs are greatly disruptive to businesses as another interviewee stated (Appendix C3). He emphasized that the provided training courses are demanding too much time, which is then missing to develop your product, determine the product market fit, and create your actual business model. Online incubation over a longer and more consistent period has nonetheless various advantages as well. As stated earlier, it is possible to reach a greater number of start-ups with such programs and provide more specific feedback on individual concerns. Interviewee D4 specified this line of thought by referring to acknowledged experts, who helped him with unique problems in a productive session of two hours. Such experts are normally not on-site in an incubator building but more likely based on another continent, which is legitimate since it is neither ecological nor efficient.

Another interesting aspect of the qualitative output has been the general validation program of the UI, trying to be as neutral as possible to enable access of incubation towards all kinds of start-ups, including smart city projects.

Recapitulated, our interview partners were as expected torn between both online and offline incubation. Both programs have advantages as well as drawbacks and individuals are favoring either one or the other. Nonetheless, the pandemic has taught us to implement such digital communication channels more easily into our daily life. The future will be based on so called hybrid models, where especially entrepreneurs will switch between customized online assistance and physical brunch meetings. The following section will elaborate on the interconnection of our quantitative and qualitative findings.

5. Discussion and Conclusion

5.1 Implications and contributions

This research aims to indicate whether smart city start-ups are more likely to survive as well as having a greater number of employees than non-smart city start-ups. As a result, the following research question was devised: *What is the effect of smart city start-ups on performance measures such as survival and size within the Utrecht Incubator?*

Theoretically, this research has several implications. The empirical analysis determined a significant positive relationship of both independent variables *smart city start-up* and *smart city score* towards the dependent variables *survival* and *size*. Colombo & Delmastro, 2002; Dvoulety et al., 2018; Eveleens, 2019; Löfsten, 2010; Westhead & Storey, 1997) found contradictory findings when it came to the influence of incubation on performance or survival. The *online* incubation did not contribute to this result compared to our assumptions, since it was insignificant in the conducted binary and score models (Table 7). The correlation matrix (Table 6) is in contrast indicating a stronger correlation of *smart city start-up* on *survival* than on *size*. Another valid argumentation of these significant positive results could be the SCI, where city depicts a “requisite criteria” to distinguish between smart city and non-smart city start-ups. According to one of the interviews, many start-ups are settling in Utrecht because it happens to be in the middle of where the co-founders live and where they can use the IT network of UU and HU.

Such circumstances are favoring *smart city start-ups* to evolve. The independent variables of the model were not the only positively significant outcomes. One of our hypotheses was that *online* incubation will enhance the performance and size of start-ups. It has been confirmed that the transformation of incubation programs was indeed positively related to the *survival* of start-ups but not smart city start-ups (Table 7). Such quantitative finding is aligning with the qualitative recognition that *online* incubation led to more applications to the incubation program and thus a higher likelihood of *survival*. *Entrepreneurial experience* is positively affecting the *survival* rate of the start-ups throughout all three models of the logistic regression. Previous studies have shown similar correlations for the growth of employment (*size*) as well (Delmar

& Shane, 2006). This is explainable because founders, who have already established a venture before, have gained valuable experiences that are easier to reproduce.

Following former research from Soetanto and Jack (2013) and Song et al. (2008), the control variable *age* has a significant positive relationship towards the independent variables *survival* and *size*. Although the robust standard errors were undermining the significance within the logistic regression model, the correlation matrix of Table 6 is underpinning the strong correlation to the independent variables and entrepreneurial experience.

This paper also provides us with a different perspective on a practical scale. The strong significances allow advising upcoming or already existent entrepreneurs to investigate ideation processes towards smarter cities. Such smart city start-ups cannot only implement a more innovative approach into cities but also attract additional know-how from outside and thus alter them into a more technological and ecological direction. Such smart city projects have to be subsidized by local governments to keep their cities attractive.

5.2 Limitations and suggestions for future research

Despite potentially interesting outcomes that have expanded research of smart city entrepreneurship, this paper has various limitations and suggestions for future studies. Firstly, it would have been useful to constitute regression analyses with financial variables such as *investment*, *revenues or assets turnover of the start-up* since performances measures of start-ups are not only being depicted by *survival* and *size*. Such diversifications would allow to contribute to a more elaborate analysis and thus a better understanding of the effect of *smart city* towards performance. Unfortunately, a financial variable was left out because of lacking data in the data sheet. Secondly, the regression models can be complemented with other independent variables such as *technical* or *economic education*. Thirdly, since the research field of the impact of online incubation towards performance of start-ups is rather, we have not been able to gather as much data as desired. The upcoming months will hopefully motivate researchers to investigate on these developments. Qualitative findings should be diversified with regards to a higher number of interviewees and multiple insights from different incubators and their experience in times of the pandemic since the focus of the paper has been more towards quantitative nature. The field of smart city, especially in terms of online incubation is still a rather new study area and is consequently offering various opportunities for future research.

5.3 Conclusion

To summarize, this research has shown a positive relationship of *smart city* towards the performance measures of start-ups. We found significant correlations for both of our independent variables *survival* and *size*. Founders and policymakers learned about necessary conditions for urban transformation, as well as striking characteristics of smart cities, which will hopefully guide them and future research to create an impact within the near future. The impact of online incubation towards ameliorated performance measures is in contrast neglectable. Moreover, this research represents an experimental attempt towards smart city entrepreneurship research and should be refined and supplemented with additional variables for further findings.

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7. Appendices

Appendix A: Operationalization table

Table 10: Operationalization table

Concept	*Indicator*	*Calculation of scores*	*Measurement*
	Dependent variables		
Start-up success	Survival	0: the start-up is no longer operating at the time of data collection 1: the start-up is still operating at the time of data collection	Binary, 0-1
	Size of the company	The number of employees working full-time for the start-up at the time of data-collection	Count, 0-∞
	Independent variables		
Smart City	Smart-city classification of Start-ups	0: the start-up is not ranked as smart city 1: the start-up is ranked as smart city	Binary, 0-1
Smart City score	Smart-city classification and progress of the start-up	0: no smart city 1: smart city 2: smart city plus one criterium 3: smart city plus two criteria 4: smart city plus three criteria 5: smart city plus four criteria 6: smart city plus five criteria Progress is calculated by the number of criteria the start-up features with +1 for every additional criterium	Categorical, 0-6
	Control variables		
Online/Offline	Online/Offline Incubation/guidance for the start-up	0: start-up has offline incubation 1: start-up has online incubation	Dummy, 0-1
Entrepreneurial experience	Former experience founding a company	0: none of the founders has prior entrepreunial experience 1: at least one founder has prior entrepreneurial experience	Binary, 0-1
Gender	The percentage of males / females	The percentage of male founders within the founding team	Ratio, 0-1
Number of founders	The number of founders	The absolute number of founders at the foundation of the start-up	Count, 0-∞
Market type	The market type of the start-up	0: the start-up works in a B2B (business-to-business) setting 1: the start-up works in a B2C (business-to-consumer) setting	Dummy, 0-1
Company age	The age of the start-up	Year of the data gathered minus the founding year, presented in months. If it has failed, take the year it has stopped minus the founding year 46: 3 years and 10 months old 87: 7 years and 3 months old	Continuous, 0-∞

Appendix B *Interview guide: Smart-City Entrepreneurship*

This interview guide was created using (Harvard University, 2017; Magnusson & Marecek, 2015) recommendations and the suggested structure. Throughout the data collection process, the interview guide was created in such a manner that it remains accessible and available to new inputs.

Business Incubation

- **Introduction**
  - Introduction of the researcher
  - Elaborating on the thesis topic
  - Assuring confidentiality
  - Allowance to record the interview to transcribe it afterwards
  - Explain to interviewee that transcript is sent for final consent

  - Brief introduction of the interviewed person and the start-up/incubator
  - Size of the company (founders, employees, freelancer)
  - When did you join the Utrecht Incubator?

- **Identification**
  - When did the idea of your business evolve? (Important to distinguish if the Incubator had anything to do with the ideation)
  - How did it evolve (Lean startup, design thinking, user-entrepreneurship)
  - Which part did the incubator play in the whole creation process?
  - Incubation process
  - During which stage of the start-up did you decide to join the incubator?
  - Specific criteria to become part of the program?
  - Was there a pitch process and who was part of the jury?
  - Why specifically this Incubator? How did you hear from it?
  - Specific preparation for the pitch based on the criteria of the incubator?

  - Could you give me some insights about the identification process (idea finding, role of incubator, why Utrecht Inc.?

- **Early-stage**
  - Specific start of the incubation program? Anything different to another incubator you might have experienced before?
  - Did you feel a strong support from the beginning?
  - How did the incubation program stop?

- Did you already sell your service/product during the business incubation?
- Differences or special program sequences?
- In what way did the incubator provide help (services, undertakings, resources)?
- Additional benefits (switching from off-line to online?
- Did the incubator also provide financial support?

- Could you provide information about the beginning of the incubation process (any differences, strong support, did the support stop, switching from offline to online incubation)

- **Continuation**

  - What was the duration of the incubation period?
  - What happened after the incubation period?
  - Does the incubation play a part in your post-incubation activities? (even indirectly)
  - Were you able to secure funding after the incubation period?
  - Did your startup expand organically (self-funding) after the incubation period?

  - Coming to the continuation section, could you tell me please more about the duration of the incubation, what happened after, did you receive funding after the incubation, etc.

- **Additional questions**

  - Online Incubation services limit the kind of entrepreneurs who can be supported since not all of them are tech savvy and thus are being excluded from applying and participating. Did you experience something similar?

  - Do you think future incubation programs will focus on being more digital than physical?

  - Did you experience specific differences between offline/online incubation?

  - In the future, entrepreneurship hubs can continue to offer a virtual structured approach to learning to reach a wider audience with their programs besides regular entrepreneurship community activities. Would you also have applied for such a virtual incubation program? How much would you be willing to pay/invest in joining such a program?

  - Have you heard about the program StartupLeap? Would you like to participate?
    - Free online start-up program
    - 10 weeks
    - Online lectures as well as online group sessions

    - Community of ambitious early-stage startup founders

- **Final remarks**

    - Anything crucial to add?
    - Are you available for further information or clarifications?
    - Explain to interviewee that transcript is sent for final consent (interpretation is researcher's responsibility)

- Thanks so much for your dedication by taking the time for this interview!

Appendix C: Transcribed interviews

Interview transcripts removed to protect personal data and due to confidentiality

Appendix D: Data set for Stata

Confy	1	0	1	4	0	1	1	1	1	62
Wheels Bn	0	0	0	0	0	0	4	0.5	0	0
Lyla Coach	0	0	0	0	0	0	1	0	1	0
Marcopolob	0	0	0	0	0	0	2	1	1	0
Goings-On	1	4	0	0	0	0	2	0.5	0	96
Perfect Pla	1	10	1	3	0	0	2	1	0	48
Closure	1	12	0	0	0	1	2	0	0	46
Learned	1	8	0	0	0	0	2	1	0	40
MoveShelf	1	6	0	0	0	1	2	1	0	48
NanoCET /	1	7	0	0	0	0	2	1	0	30
BCP Soluti	0	0	0	0	0	0	2		0	0
BeThePixe	0	0	0	0	0	1	1	1	0	53
Postzerolat	1	1	1	4	0	0	1	1	0	57
Holomoves	1	4	0	0	0	0	2	1	0	30
Hoofdmaat	1	2	0	0	0	1	2	0.5	1	34
Foodapp	0	0	0	0	0	0	2	1	1	24
Launch AI	1	0	0	0	0	0	2	1	0	36
Nederland	0	0	0	0	0	0	1	1	0	9
Driemers	1	0	1	4	0	1	1	1	1	57
Teached	0	0	0	0	0	1	1	1	0	21
Zero Touch	0	0	0	0	0	1	3	1	0	18
Remind2Ch	1	2	0	0	0	1	1	1	1	37
VlogOut	1	2	1	4	0	1	2	0	0	54
Slim	0	0	0	2	0	0	2	1	0	16
LalaLand	1	0	0	0	0	0	2	1	0	29
Swapify	0	1	0	0	0	0	1	1	1	38
One Care F	1	2	0	0	0	0	1	1	0	154
StudyApp	1	0	0	0	0	0	1	1	1	37
LIV	0	0	0	0	0	0	1	1	0	0
Stack	1	10	1	3	0	0	1	1	0	24
ProductPin	1	15	1	3	0	0	1	1	0	27
Tailo (cmoti	1	0	0	0	0	0	1	1	0	18
TechCub	0	0	0	0	0	0	1	1	0	5
ESNA Heal	1	1	0	0	0	0	1	1	0	24
Hooray	1	10	0	0	0	1	2	1	0	30
Nederland	1	15	1	4	0	1	3	1	1	40
EatMyRide	1	7	0	0	0	0	3	1	1	26
Smart Fligh	1	1	0	0	0	1	2	1	0	28
NextLevelF	1	1	0	0	0	1	2	1	0	51
Vurdere	1	10	0	0	0	1	2	1	0	94
FrAsk	0	0	0	0	0	0	2	1	1	11
Brainial	1	10	0	0	0	1	2	1	0	24
AVA	0	0	0	0	0	0	1	0	1	18
Keystone M	1	6	0	0	0	0	1	1	0	23
Kokeroo	1	2	1	4	0	0	2	1	0	0
Generative	0	0	0	0	0	0	3	0.66	0	0
Valergy Sy	0	0	0	0	0	0	1	1	0	0
Circle of Pa	1	1	1	5	0	0	3	1	1	19
Mindshape	1	0	0	0	0	0	1	0	1	18
Buxon	0	0	0	2	0	0	1	1	1	24
Sprintgrour	1	1	0	0	0	1	2	1	1	136
Nyamazela	0	0	0	0	0	0	1	1	0	216
PACT care	1	3	0	0	0	0	1	1	0	37
MoodRequ	0	0	0	0	0	0	2	0.5	1	0
Travelfreak	0	0	0	0	0	0	1	1	1	0
Houtpost	1	1	1	4	0	0	1	1	1	6
Educadia	1	0	0	0	0	0	1	1	1	0
XXL Tool /	1	2	0	1	0	0	2	1	0	30
Ubotech	1	0	0	0	0	0	2	1	1	0
Dishmakers	0	0	0	0	0	0	1	1	1	0
PACE	0	0	0	0	0	0	1	1	0	0
QUIBBLE	0	0	0	0	0	0	3	1	0	0
Scinvivo	1	5	0	0	0	0	2	0	0	46
Re | perfus	0	0	0	0	0	0	2	1	0	0
CherryPickl	0	0	0	0	0	0	3	1	0	0
Equality	0	0	0	0	0	0	2	0.5	0	0
Preimure	0	0	0	0	0	0	1	1	0	0
Clue to the	1	1	0	0	0	1	2	1	0	26
Nanovio Bi	0	0	0	0	0	0	3	1	0	0
MLA DIAGI	1	3	0	0	0	0	3	0.66	0	25
WaveTronic	1	5	0	0	0	0	2	1	0	35
Deltas Plar	1	1	0	0	0	0	2	0.5	0	0
BikeFlip	1	6	1	4	0	1	5	0.4	1	23
Näpp	1	1	1	3	0	0	2	0	1	36
ScienceToo	1	0	1	2	0	1	3	1	0	25
Pivot	0	0	0	0	0	0	4	1	0	0
Serve Supp	1	3	1	5	0	1	3	1	0	26
ProtectYou	0	0	0	0	0	0	3	0.66	1	0
Biserja	0	0	0	0	0	0	5	0.4	0	0
Ikauros	1	0	1	4	0	1	1	1	1	19
OYA	0	0	0	0	0	0	1	1	0	0
SatCat	0	0	0	0	0	0	1	1	1	0
LegalKit	0	0	0	0	1	0	1	1	0	0
Wintersol E	1	1	1	5	1	1	1	1	1	20
KidsClass	0	0	0	0	1	0	3	0.33	0	0
Pack of Pe	1	2	1	3	1	0	2	1	1	23
Wheelflow	1	0	1	6	1	0	2	1	1	36
Refillt	0	0	0	0	1	0	2	1	0	0
Squad Mob	1	3	1	5	1	1	2	1	1	28
Pyrolyze	1	3	1	5	1	1	2	1	0	40
Buroup	0	0	0	0	1	0	4	1	0	0
Jomia	0	0	0	0	1	0	2	0.5	1	0
MySafariDe	1	1	0	0	1	0	2	1	0	43
Bytle Ds	0	0	0	0	1	0	1	1	0	0
Otira	1	0	0	0	1	1	1	1	0	0
Parkupkeep	1	1	0	0	1	0	1	1	0	34
Underdogs	1	12	1	3	1	0	2	0.5	1	25
Fields	0	0	0	0	1	0	1	1	0	0
DIMIK	1	3	0	0	1	0	3	0.66	0	24
SportJobby	1	0	0	0	1	0	2	1	0	0
Sportcircle	1	1	0	0	1	0	2	1	1	0
Chex	0	0	0	0	1	0	4	1	1	0
Youwi	0	0	0	0	1	0	2	1	1	0
Happy Plac	0	0	0	0	1	0	3	0	1	0
Massage2r	0	0	0	0	1	0	1	1	1	0
Yumii	0	0	0	0	1	0	2	1	1	0
Valor Metric	1	2	0	1	1	0	3	1	0	26
Ecytes (Ina	0	0	0	0	1	0	2	0.5	0	0
GraphPolar	1	0	0	0	1	0	1	1	0	0
Sportify	0	0	0	0	1	0	2	1	0	0
DigiWolf	0	0	0	0	1	0	1	1	0	0
Codean	1	3	0	1	1	0	1	1	0	17
DOCTO	0	0	0	0	1	0	4	0.75	0	0
MedTag	0	0	0	0	1	0	2	1	0	0
Elementa	1	1	0	0	1	0	2	0.5	0	5
PRAC / Acı	1	6	0	0	1	0	2	0	0	20
WeFIT	0	0	0	0	1	0	1	1	0	0
This Look	0	0	0	0	1	0	2	0.5	0	0
ParcelP	1	1	1	5	1	1	2	1	0	14
Thank Link	1	0	1	5	1	0	1	1	0	8
BController	0	0	0	0	1	0	1	1	1	0
Orgonex	0	0	0	0	1	0	3	0.33	0	0
Daphne Te	0	0	0	0	1	0	2	1	0	0
Jawsaver	1	2	0	0	1	0	2	0.5	1	12
DataHorse	1	1	1	0	1	0	1	0	0	6
AOKI Medi	0	0	0	0	1	0	1	1	0	0
MeTex.ai	0	0	0	0	1	0	2	1	0	0
ImageFun	0	0	0	0	1	0	2	1	0	0
RRB Tech	0	0	0	0	1	0	1	1	0	0
Iomete	1	1	0	2	1	0	2	1	0	9
Entor	0	0	0	0	1	0	3	0.66	0	0
Sprinque	1	4	0	1	1	1	1	1	0	18
Localdesk	1	2	1	4	1	0	2	1	0	11
Pili	1	4	1	3	1	0	2	1	0	15
ABL sustai	1	3	0	0	1	0	3	0	1	0
Popup Car	1	3	0	3	1	1	2	0.5	1	11
BarberCity	0	0	0	0	1	0	1	1	1	0
Mijn Master	1	2	1	5	1	0	1	1	1	0
The Wolves	0	0	0	0	1	0	1	1	1	0
Fair Urban	1	3	1	6	1	0	2	0.5	0	16
StudentDe	1	3	0	1	1	0	2	1	1	42
eVRgreen	1	1	0	2	1	0	1	0	0	11
Ecova / Go	1	2	1	4	1	1	1	1	0	28
U-Lunch / I	1	0	0	2	1	0	1	0	0	3
DoMedia	0	0	0	0	1	0	3	1		0
DockPot	0	0	0	0	1	0	2	1		0
Healers	0	0	0	0	1	0	1	1		0
Rare	0	0	0	0	1	0	1	1		0
Vibes Tech	0	0	0	0	1	1	2	1		0
Ecompacto	0	0	0	0	1	0	1	1		0
I'M TechMe	0	0	0	0	1	0	1	1		0
Cheress Te	0	0	0	0	1	0	1	0		0
Technotitia	1	2	0	0	1	1	1	1	0	46
BeCurious	0	0	0	0	1	0	2	0.5		0
Your Nutriti	0	0	0	0	1	0	1	1		0
InterTwined	0	0	0	0	1	0	1	1		0
Goodword	0	0	0	0	1	0	2	1	0	0
TraceLinq	1	2	0	0	1	0	2	1	0	12
MeterInsigh	1	2	1	2	1	0	2	1	0	35
Friday Ener	1	5	1	5	1	0	2	1	0	24
PatientenB	1	4	0	2	1	1	2	1	0	58
Cyan Reef	1	2	1	4	1	0	2	0.5	1	21
Digidok	1	7	0	2	1	0	2	0.5	0	22
Amatec	1	4	0	1	1	0	1	1	0	87
Mercuso	1	8	1	6	1	0	2	0.5	0	28
Goin'	1	9	1	3	1	1	2	1	0	35
Urbango	1	5	1	5	1	0	2	1	1	6
Motoshare	1	12	0	1	1	1	2	1	1	68

Appendix E: Do-file Stata

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. import excel "\\Client\H$\Documents\BDE & E%20\Master Thesis\Stata data\Data

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