



Preventing falls among the community-dwelling elderly

Analyzing the impact of fall prevention programs and evaluating the applicability of a Health Impact Bond

Master Thesis by J.J.A van Berckel



strategy&

**Albert
Schweitzer**
ziekenhuis



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Analyzing the Impact of Fall Prevention Programs and Evaluating the Applicability of a Health Impact Bond

By
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Preface

This study is conducted in light of graduation from the master program ‘Engineering and Policy Analysis’ at the Delft University of Technology. This research, set up in collaboration with Strategy& and the Albert Schweitzer Hospital (ASZ), focusses on analyzing the effectiveness of fall prevention programs and evaluating the applicability of a Health Impact Bond.

The research structure can roughly be divided up into two discrete phases. The first involved the understanding of the Dutch healthcare system and the problems faced by actors involved in either preventing falls or treating the injuries caused by them. In this orientation phase, I conducted numerous interviews with enthusiastic and helpful people. Also, I decided to walk along for one day at the Emergency department and one day at the Geriatric Department of the ASZ. During these days, I was able to see the problems of falls in the elderly. I want to thank Annemarie, Maaike and Marianne for giving me this great opportunity and to show me the severity of this problem. In addition, I want to thank Arno, Marcel, Marieke and Annemarie for including me in your multidisciplinary meetings in which I learned a great deal about fall prevention. I want to express my sincere gratitude to Annemarie (ASZ) in particular as she has provided essential input for my thesis and brought me into contact with other experts in this area.

The second phase involved the analysis to determine the effectiveness of the fall prevention programs and to evaluate the applicability of a Health Impact Bond to encourage implementation of these same programs. I could not have successfully completed this phase without valuable input from Arno, who I admire for his passion to improve the lives of elderly and his perseverance to set up these fall prevention programs. Also, the interview with Saskia from VeiligheidNL contributed greatly to my thesis. Via Nanni Ruedisueli (ASZ), I was able to get in contact with the information security officer of privacy to get permission to use an anonymized dataset from the ASZ, and with Robin van der Vlies who provided the hospital dataset to me. Without you two I would not have been able to do this rather unique research as it is hard to acquire such a dataset.

Writing a thesis for university whilst actively collaborating with a consultancy and care providers proved to be both challenging and rewarding to me personally. Although it required a lot of energy to constantly manage and fulfill the expectations of the involved parties (TU Delft, FysioDordt, ASZ, and Strategy&), the extra insights gained by collaborating with so many different experienced individuals were truly worthwhile. Conducting this research has fueled my ambitions to continue working with healthcare-related topics.

This research could not have been conducted without the support of certain people around me. Firstly, I would like to thank my two university supervisors Jos and Haiko for their guidance and advice throughout this research. Secondly, I am indebted to my internship-supervisor Umar Ikram, for helping me understand the complex Dutch healthcare sector and for helping me to find a suitable topic in the starting phase of my research. Lastly, I would like to thank two people in particular who helped and supported me throughout the whole research process. My mother, for her encouragements and for reminding me to keep my head up at times when I was struggling; and my girlfriend Amy, for helping me keep focus without losing touch of the joys of life. Thank you all very much.

By finalizing this thesis, I realize that I am also approaching the end of my life as a student. I experience this both as extremely gratifying as well as rather challenging. Although the road ahead is full of uncertainties, I feel privileged and strengthened by the deep friendships and unique experiences I was granted throughout these truly mesmerizing years as a student.

Joost van Berckel, Delft, July 2019

Executive Summary

Background

The elderly population in the Netherlands is responsible for about half of the total healthcare expenditures. Due to an aging society, these costs will only increase in the future, and it will be a challenge to maintain high-quality healthcare while at the same time controlling the rise of healthcare spending. Falls are the most common and often overlooked cause of injury in the elderly, and these incidents are a significant cause of morbidity.

Last year, fall incidents caused 102.000 traumas in the Netherlands, of which 69.700 were severe injuries that had to be treated in the emergency department. Due to functional loss and depleted reserves, the risk of another fall increases after a hospitalization. This vicious circle causes functional impairment, long-term pain, and high economic costs. Hospital expenses in the Netherlands associated with falls were estimated to be around 912 million euros in 2015 and are expected to rise to 1.3 billion euros in 2030.

Research objective

Fall prevention programs hold great promise to improve quality of life among older adults and to decrease healthcare expenditures. By reducing the number of fall incidents, community-dwelling elderly can live at home for a more extended period, which will lower healthcare costs as expensive 24-hour care at nursing homes is not required. However, there are substantial barriers for (entrepreneurial) people working in the elderly care to set up fall prevention programs, due to the size of the investments required, the uncertainty of the parties about the potential benefits from the reduction in healthcare expenditures and the divergence of interests within our fragmented healthcare system.

Hence, a method to assess the effect of fall prevention programs is needed, and, if these programs indeed appear to have a positive effect on the healthcare costs, there might be possibilities to use an innovative financing structure, such as a Health Impact Bond (HIB), to encourage the implementation. A HIB is a performance-based instrument by which the financial risk shifts from local implementers to investors. Before an investment is made, investors and parties, where the savings end up (often governments and health insurers), need to agree on performance indicators. Also, these parties need to reach a consensus about the evaluation method to assess the performance of the programs. When the healthcare interventions have been implemented and an independent assessor determines that the performance targets have been met, investors are repaid their capital plus a return. However, as there is no method available to assess the effectiveness of fall prevention programs once implemented, the possible reduction in the number of fall incidents and associated decreased healthcare costs are unknown. As a result, stakeholders, such as health insurers, are not convinced that fall prevention programs reduce healthcare costs and are unwilling to take part in a HIB.

During this research, a method is developed to determine the effect of fall prevention programs on the number of injurious fall incidents and related healthcare expenditures of community-dwelling elderly. With this method, the economic feasibility of a HIB for fall prevention programs can be assessed. Other barriers for setting up these programs using a HIB regarding governance and law will be identified. The research question is:

"How can the effect of fall prevention programs on the number of injurious fall incidents and healthcare costs of community-dwelling elderly be determined in order to explore the applicability of a Health Impact Bond?"

This thesis focusses on two main elements: the effect of fall prevention programs and the applicability of a HIB.

The effect of fall prevention programs

A case study approach is used in order to answer the first part of the research question. In this case study, patient-specific data of the Albert Schweitzer Hospital (located in Dordrecht) is analyzed to determine the effectiveness of programs implemented in ten physiotherapy clinics in Dordrecht-East. It is unpractical and unethical to track the healthcare history of older adults who participated in these fall prevention programs. Therefore, the Difference-in-Differences (DID) design was used to assess the effect of the fall prevention programs on the elderly population of Dordrecht-East. This DID method calculates the difference in outcomes between two populations, one population exposed to the treatment and another population not exposed to the treatment (the control population), before the fall prevention programs were implemented and after implementation. The difference between those two differences is the estimated effect of the intervention. This method is used to determine the effect of the fall prevention programs on both the number of injurious fall incidents and healthcare costs.

Many expert interviews were required in order to determine the effect of the programs and to assess the economic feasibility of a HIB. By doing a literature review and two interviews with an Emergency Physician, it was possible to select and classify the diagnoses related to fall incidents in the hospital dataset. In another interview, with the local implementer of the programs in Dordrecht, information was gathered about the characteristics of the participants of the fall prevention programs as well as information about the implementation- and operational costs. The yearly operational costs of the fall prevention programs are around 99.717 euro, and 42.865 euro was spent in the years before implementation to screen elderly and to develop the programs.

The results of the case study show that the implemented fall prevention programs in Dordrecht-East have reduced 55 injurious falls in one year. However, the estimated effect of the programs on the risk of falling varies quite strongly (between 122 (prevented) falls and -11 (prevented) falls).

The same Difference-in-Differences design was unfit to assess the effect of fall prevention programs on the hospital expenses due to considerable differences in costs between the injuries caused by falls. In order to assess the effect of fall prevention programs on the hospital expenditures, replication of this research is needed using a larger dataset, including a more extensive intervention- and control area. The research is easily replicable as the data processing and analyses have been done in a python model which can process other hospital datasets with only minor adaptations to the code. However, it remains challenging to collect the required hospital data due to privacy and confidentiality issues. Systematic reporting of the number of falls, the type of injuries, and the total healthcare costs of the injuries per region should be encouraged.

The applicability of a Health Impact Bond

The Dutch Consumer Safety Institute has estimated the average total healthcare costs of a fall incident per age group with data from their Injury Surveillance System. The results of their analysis in combination with the results from the DID method (effect on the number of fall incidents) is used to determine the effect of the programs on the total healthcare costs. The yearly total cost reduction is estimated to be 322.000 euro due to the implementation of the fall prevention programs in Dordrecht-East. These results have been reviewed by an expert in the field of fall prevention.

Therefore, assuming that the average estimated effect of the fall prevention programs is correct, fall prevention programs have proven to be an effective intervention. The intervention results in a reduction of healthcare costs that far outweigh the implementation- and operational costs of these

programs (142.582 euro). The reductions in healthcare expenditures are sufficient, not only to cover the required organizational costs and to be able to repay the investor, but also to finance an investment when funding has ended. With enough health benefits saved, the programs can continue to run this way, without the need for private investors.

However, courage from investors, local entrepreneurs, and payers is needed to set up the first HIB. This HIB-cooperation is desperately needed, because making performance visible in healthcare is difficult, paying out the savings achieved to investors is still unexplored territory and stakeholders need to agree on an evaluation method to determine the effect of the programs. The evaluation method developed in this thesis can provide a basis to help in negotiations between these stakeholders to determine the outcome measurements and evaluation method.

An expert on fall prevention programs and HIBs, working at the Dutch Consumer Safety Institute, provided information about the possible legal- and governance barriers when implementing programs using a HIB. One of the governance barriers is that implementation using a HIB will be hard as a complex network of actors with different incentives is involved. For example, health insurers are uncertain about the benefits of a HIB. These essential stakeholders are unsure about the actual savings, as a result of the implementation of the fall prevention programs, on the short- and long term. They expect that savings in the short term will be nullified by higher costs of care in the last year of the life of an elderly. In addition, they argue that any loss in revenue is compensated by providing extra care in other departments of the hospital as there is a strong production incentive in the current Dutch healthcare system.

Apart from governance, some legal barriers need to be surmounted as health insurers and care offices cannot pay out possible health profits to private parties. Funds from the municipality through the Social Support Act (WMO) are not sufficient to cover the operational- and implementation costs of fall prevention programs. However, exceptions regarding this topic can be made by the Ministry of Health, Welfare and Sport (VWS) and they should facilitate that these exceptions are easily granted.

If these barriers can be overcome, a HIB can provide many opportunities to facilitate the implementation of programs in municipalities across the Netherlands, which will improve the quality of life of elderly within Dutch society. By using this innovative structure, the financial risk of implementation is shifted from local implementers to the investors, which encourages these implementers to develop and implement fall prevention programs. Moreover, as older adults are not required to pay for the fall prevention programs, they are more likely to participate. These two main advantages of a HIB might facilitate successful implementation in many regions across the Netherlands, resulting in a higher quality of life for older adults and at the same time lower healthcare expenditures. However, only through open, sustained, and coordinated efforts by both policymakers and stakeholders involved in elderly care, the HIB has a chance to become a leading instrument to implement fall prevention programs in the Netherlands.

Recommendations for further research

Future research as a result of this case study should focus on further improvement of the method to evaluate the effectiveness of the fall prevention programs. This can be done by assessing the impact of fall prevention programs in other areas using the python model and DID-method. It is also possible to test the DID design to evaluate other outcome measures such as the effect of the programs on the number of deaths, operations and hospital days, and the readmission rate. In addition, the model might be useful to assess other interventions to prevent falls. By using and adapting the model, incremental improvements can be made. Furthermore, the current model should be discussed with payers in order to make improvements. Another suggested study may be to determine the additional benefits of fall prevention programs such as less informal care, less loneliness, or improvement of the quality of life.

Future research regarding the use of a HIB ought to concentrate on removing governance- and legal barriers which have been identified in this study. Another important aspect to analyse may be the organizational costs of a HIB, such as the payment of the independent assessor, for financial- and legal services or advice, and of the local implementor or intermediary. Also, research can be done to examine which (legal) elements should be included in a contract between the investors and payers, and between payers and local implementers or executors. Finally, other types of outcome measures should be reviewed that can contribute to the fairness of the contract.

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List of abbreviations

ASZ	Albert Schweitzer Ziekenhuis (hospital)
CBS	Centraal Bureau of Statistiek (Central Bureau of Statistics)
DBC	Diagnose Behandeling Combinatie (Diagnosis Treatment Combination)
DID	Difference-in-Differences (method)
DOT	DBC's op weg naar Transparantie (similar to DBC)
ED	Emergency Department
HC	Healthcare
HIB	Health Impact Bond
LIS	Letsel Informatie Systeem (Injury Surveillance System)
NFPP	Nijmegen Fall Prevention Program
NZa	Nederlandse Zorgautoriteit (Dutch Healthcare Authority)
RCT	Randomized Controlled Trial
SCP	Sociaal en Cultureel Planbureau (The Netherlands Institute for Social Research)
SES	Socioeconomic status
SIB	Social Impact Bond
VWS	Ministerie van Volksgezondheid, Welzijn en Sport (Ministry of Health, Welfare and Sport)
WLS	Weighted Least Squares (regression)
WLZ	Wet Langdurige Zorg (Long-Term Care Act)
WMO	Wet Maatschappelijke Ondersteuning (Social Support Act)
ZVW	Zorgverzekeringswet (Health Insurance Act)

1

Introduction

In the Netherlands, one in every five inhabitants is aged above 65 (hereafter referred to as elderly or older adults) and this relatively small part of the population is responsible for about half of the total healthcare expenditures. Moreover, the elderly population is expected to grow to 25% of the total population in 2030 (Post, Huijsmans, Luijk & Gusdorf, 2018). A situation called 'double societal aging' exists: the life expectancy is increasing and a growing share of the population is becoming retired. An aging society will put pressure on the financing of the national healthcare system and results in personnel shortage. It is a challenge to maintain high-quality healthcare while at the same time controlling the rise of healthcare spending (Auping, Pruyt & Kwakkel, 2015).

Growing old is a natural, irreversible process that goes together with a greater need for healthcare. Elderly who get ill or injured tend to stay for an extended period in the hospital resulting in high healthcare expenditures and vulnerability. Within three months of admission, a large proportion of these older adults die or develop a permanent loss of function (Franchi, Nobili, Mari, Tettamanti, Djade, Pasina, & Marcucci, 2013). Falls are the most common and often overlooked cause of injury in the elderly. Also, fall incidents are a significant cause of morbidity and mortality and are mostly preventable (Olij, Ophuis, Polinder, Van Beeck, Burdorf, Panneman & Sterke, 2018).

National- and international literature showed with randomized controlled trials (RCTs) that well-designed programs could prevent falls (El-Khoury, Cassou, Charles & Dargent-Molina, 2013). On that basis, fall prevention programs have been implemented in some municipalities in the Netherlands. However, it is hard to implement fall prevention programs due to the size of the investment required, a complex network of actors that are involved, and because there is no method available to assess the impact of fall prevention programs once implemented. Therefore, it is not clear what the real benefits are for stakeholders such as health insurers, governments, and municipalities (Soeters & Verhoeks, 2015).

In some cases, municipalities provide subsidies to help the implementation of a fall prevention initiative, but these subsidies are hard to acquire (Olij et al., 2018). With the current Dutch healthcare system, there are not enough options for local implementers to receive funding to set up these fall prevention programs (Bassant, 2016).

ZonMW (a Dutch research institution) and the Ministry of Health, Welfare and Sport have recently released promising research for a new financing model for healthcare interventions: the Health Impact Bond (Soeters and Verhoeks, 2015; Kloet, Kuiper, Toet, Coppens, Van Oordt-Jansen, Stapersma, Van Zoest, & Rühl, 2017). This innovative financing structure is a performance-based instrument by which the financial risk shifts from local implementers to investors. Before an investment is made, investors and parties where the savings end up (often governments and health insurers) need to agree on performance indicators and the evaluation method. When the healthcare interventions have been implemented, and an independent assessor determines that the performance targets have been met, investors are repaid their capital plus a return (Van Es, Houben, & Nijeholt, 2016).

Before one can consider using such an innovative financing instrument, there are two requirements that have to be met. The first one is that the fall prevention programs must have a positive effect on the quality of the lives of older adults resulting in a measurable decrease in the number of injurious fall incidents and healthcare costs. The second requirement is that a method should be available to evaluate the effect. Therefore, this study aims to develop a method to assess the effect of fall prevention programs on the number of injurious fall incidents and hospital expenditures of community-dwelling elderly. If these programs have a measurable positive impact on the elderly population, the possibilities to encourage local entrepreneurs to implement fall prevention programs using a Health Impact Bond can be explored.

2

Research problem

2.1 Problem statement

2.1.1 The impact of fall incidents on older adults and society

The Dutch institute VeiligheidNL (2017) estimated that falls caused 102.000 traumas in the Netherlands, of which 69.700 were severe injuries that had to be treated in the emergency department. As many as 3.849 older adults died as a result of a fall in 2017. According to Gibson (1987), a fall can be defined as an event, which results in a person coming to rest inadvertently on the ground, not because of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, or an epileptic seizure.

A fall can have a tremendous impact on the life of an older adult. About 30% of people with a hip fracture will die in the following year and many more will experience significant functional loss (Brauer, Coca-Perraillon, Cutler & Rosen, 2009). Due to functional loss and depleted reserves, the risk of a fall increases after a hospital visit and an older person is more likely to end up in the hospital again. Older people often end up in a vicious circle causing functional impairment, long-term pain, and high economic costs (El-Khoury et al., 2013). This vicious circle is shown in the figure below.

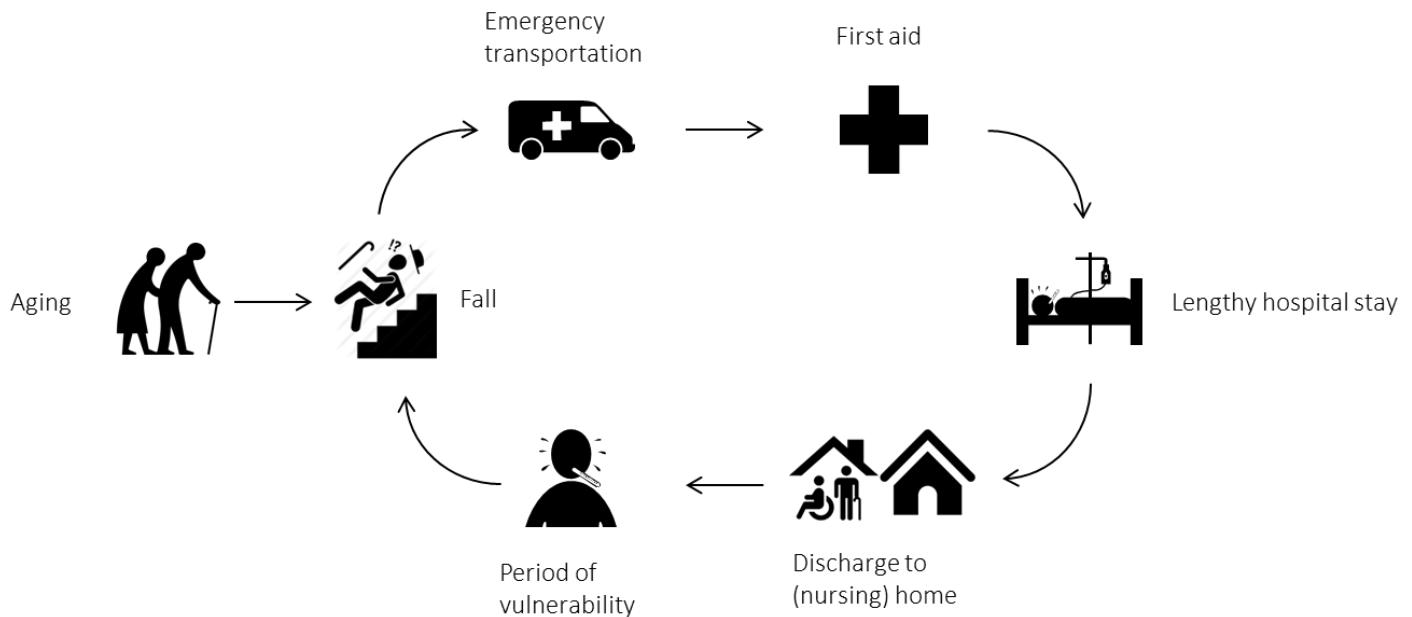


Figure 1: Vicious circle of elderly patients

Elderly can develop 'fear of falling', which is an ongoing concern about falling and leads to less daily activity and weaker muscles (Legters, 2002). Such distress can cause a similar 'period of vulnerability' (as described in figure 1) and a higher risk to fall again. Thus, fall incidents resulting in severe- and even minor injuries are essential to consider as these will accelerate functional decline and increase the risk of placement in a nursing home. By reducing the number of fall incidents, community-dwelling elderly

can live in their own homes for a more extended period which will improve their quality of life and will lower healthcare expenditures as expensive 24-hour care at nursing homes is not required (El-Khoury et al., 2013).

Falls in the elderly also have an impact on society as a whole. Hospital expenditures in the Netherlands associated with falls are estimated to be around 780 million euros in 2013, 912 million euros in 2015 and are expected to increase to 1.3 billion euros in 2030 (ZonMW, 2017). The most common injuries due to falls in persons aged 65 years or older are superficial injuries, hip fractures, upper-six extremity fractures, and traumatic brain injury (Hartholt, Van der Velde, Loosman, Van Lieshout, Panneman, Van Beeck, Patka & Van der Cammen, 2010).

2.1.2 The current barriers for implementers to get funding for fall prevention programs

In the Dutch healthcare system, healthcare providers are expected to develop interventions to prevent falls in the elderly. However, the financial benefits of these investments often do not end up with the care providers themselves. On the contrary: the party that receives the benefit is often the health insurer, the municipality, or the government. However, these stakeholders are not always interested in investing in prevention projects due to a divergence of interests within the Dutch fragmented healthcare system (Tummers, 2013).

Currently, most health insurance policies do not (fully) cover the expenses made by elderly to participate in fall prevention programs (Hendriks, Van der Velden, Van Houten & Meinardi, multidisciplinary meeting 1, 2018). In some cases, municipalities provide subsidies to help the implementation of a fall prevention initiative, but these subsidies are hard to acquire (Hendriks, interview, 2019). For several years now, national institutes who focus on fall prevention, such as VeiligheidNL, have tried to convince insurers and the Dutch government to compensate older adults for participating in these programs (Kloet, interview, 2019). However, there is often no incentive to invest in prevention because it is unclear what the benefit will be for the insurer and because of the ‘wrong pockets problem’. The latter is a situation in which the party that bears the cost of implementing a program does not receive the primary benefit (Harchaoui, Van der Meer & Zafar, 2016).

The current Dutch healthcare system is based on payment per medical procedure, which results in a strong production incentive. This does not encourage prevention: a reduction in fall incidents will decrease the revenue of a hospital. Another problem is that stakeholders, such as the government, municipalities, and health-insurers, are unable to share the benefits from fall prevention programs or are unaware of these possibilities to reduce healthcare costs (Kloet et al., 2017). Thus, it is not likely that fall prevention programs will be part of the ‘standard’ insurance policy in the Netherlands in the coming years. This ‘standard’ insurance policy means that every individual participating in a fall prevention program, regardless of the type of health insurance, will be fully reimbursed (Kloet, interview, 2019). Hence, there are not enough options for local implementers of fall prevention programs to get funding. There is a need to develop a method to assess the effect of fall prevention programs and, if these programs have a positive effect on the healthcare costs, there might be possibilities to use innovative approaches to encourage the implementation.

2.2 Literature review

As introduced in chapter one, this thesis focuses on two main elements: to assess the impact of fall prevention interventions and to review how to encourage the implementation of the programs (assuming that there is an effect). A literature review will be done on both subjects.

A wide range of interventions to reduce fall incidents and to break the vicious circle of 2.1.1 have been assessed in national- and international literature. These interventions and their results will be described in the next section (2.2.1). In addition, a literature review has been done to elaborate on possible innovative funding structures that encourage the implementation of fall prevention programs (section 2.2.2).

2.2.1 Interventions to prevent falls in the elderly

Gillespie, Gillespie, Robertson, Lamb, Cumming, and Rowe (2003) assessed a wide range of interventions to prevent falls in the elderly. The following interventions are considered successful: balance exercises and muscle strengthening, withdrawal of medication, home hazard assessment, and individually prescribed care for elderly with a history of falling. Campbell, Robertson, Gardner, Norton, and Buchner (1999) demonstrated how the withdrawal of Fall Risk Increasing Drugs (FRID) reduces falls. According to Yan (1998), Tai Chi (a form of Chinese martial arts) practice may help senior citizens improve dynamic balance control, which reduces hospital admissions.

A study by Olij et al. (2018) evaluated several different studies providing an overview of fall prevention programs and their effect. The study involved programs for fall prevention through exercise, home assessment, medication adjustment, and multifactorial programs. According to the study, older adults with an increased risk of falling are ineffectually traced, and only a small proportion of the high-risk elderly population receives a referral to fall prevention programs. Besides, the elderly show little willingness to cooperate. The latter might be remedied by a combination of government information, advice from care providers, and the removal of financial obstacles (Olij et al., 2018). Moreover, the fall prevention programs offered in the Netherlands are highly fragmented and often unknown to the senior citizens or challenging to reach (Kloet et al., 2017).

In the Netherlands, a few programs have been developed that focus on muscle strengthening and balance exercises. An example is the program 'Vallen Verleden Tijd' or Nijmegen Falls Prevention Program (NFPP) (RIVM, 2017). NFPP is a 10-week course consisting of several balance exercises and focuses on teaching an older adult how to act in the event of a fall. This program is implemented in some municipalities in the Netherlands and even caught international attention (Schuetze, 2018). The impact of the program has been assessed in two different RCTs showing that the programs reduce the fall rate by approximately 40% (Weerdesteyn, Rijken, Geurts, Smits-Engelsman, Mulder & Duysens, 2006; Smulders, Weerdesteyn, Groen, Duysens, Eijsbouts, Laan & Van Lankveld, 2010).

As this program had good results in these small scale RCTs, several programs have been implemented throughout the Netherlands. However, setting up large scale RCTs have proven to be ethically and practically troublesome, and currently, there is no other evaluation method available (Soeters & Verhoeks, 2015).

Policymakers are well aware of the problem of falls in the elderly and several promising programs have been developed that might reduce the number of fall incidents. However, local implementers are inadequately encouraged to set up fall prevention programs. As there is no method available to assess the effectiveness of fall prevention programs once implemented, the possible reduction in the number of fall incidents and healthcare costs are unknown. As a result, stakeholders, such as health insurers, are not convinced that fall prevention programs reduce healthcare costs and are unwilling to help with the required investment (Tummers, 2013).

Thus, many interventions have been developed and some of these interventions have been implemented. However, there are substantial barriers for (entrepreneurial) people working in the elderly care to set up fall prevention programs due to the size of the investments required, the uncertainty of the parties about the potential benefits from the reduction in healthcare expenditures, and the divergence of interests within our fragmented healthcare system. There might be great opportunities to enhance the quality of life of older adults and to reduce healthcare costs. Nowadays, only 1% of older adults participate in fall prevention programs (Olij et al., 2018).

2.2.2 Innovative financial instruments

Assuming that the programs reduce the number of falls and healthcare costs (which will be evaluated in this thesis), an innovative funding approach may be interesting to explore in order to give local implementers new funding option.

2.2.2.1 Social Impact Bond

Soeters and Verhoecks (2015) recently analyzed several new financial structures to fund prevention programs, one of which is a Social Impact Bond (SIB). According to Gustafsson-Wright, Gardiner, and Putcha (2015, p.4), a SIB is a model in which private investors put up capital to fund a social intervention and governments repay the investors only if an agreed-upon outcome is achieved. In 2016, around 50 SIBs were launched worldwide and more SIB partnerships are created each year. The goal of a SIB is to reduce costs and to improve society. For example, a SIB can be used to provide funding for programs to reduce unemployment or criminal activities (Vennema, 2016). An example of a SIB structure is presented in figure 2:

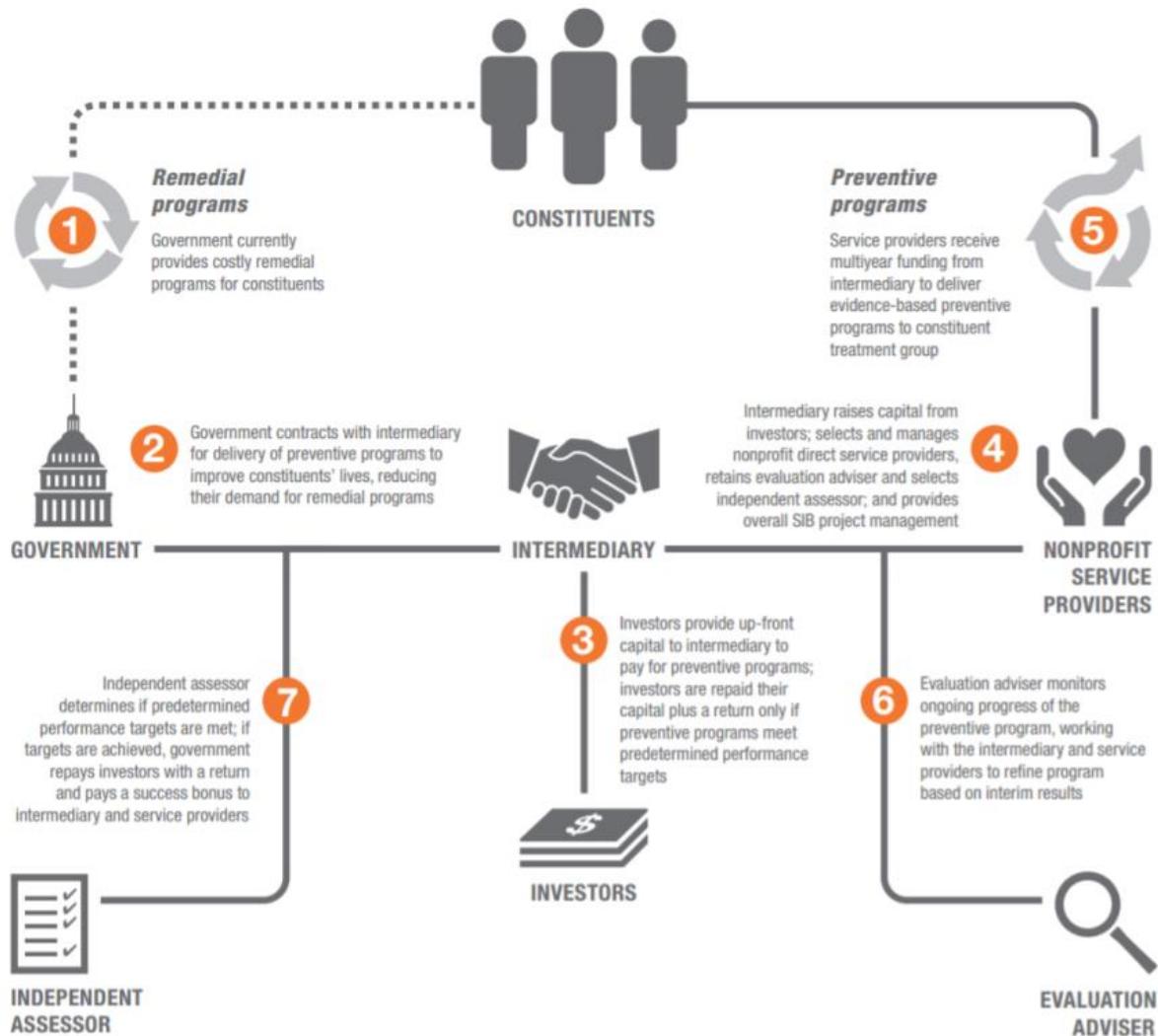


Figure 2: A concept version of a Social Impact Bond (Lower-Basch, 2014)

Constituents are the inhabitants that participate in a program in order to improve the quality of their lives. The nonprofit service providers will provide the services and the investors provide the capital required for these interventions. The government, or any other party that will benefit financially from the service, will agree on pre-determined outcome measures with the investors. The independent assessor determines if the predetermined targets are met and the investor receives (part of his) investment back if those outcomes are achieved. The intermediary controls the entire process and has to bring all the stakeholders together and evaluates (together with an evaluation advisor) the progress to refine the program based on interim results (Vennema, 2016).

In the Netherlands, the first SIB 'Social Hospital' has been implemented in 2017. This social enterprise enables service providers to help 250 (troubled) families with better and cheaper plans to solve their

problems in the coming five years. Before this intervention was implemented, the average costs per troubled family were estimated to be 104.000 euro. These families often have several problems to cope with at the same time concerning money, working life, raising children, mental- and physical problems. Social-Hospital assists in solving these problems and in improving the lives of the targeted families. By helping these families and by staying loyal and honest, the members of the family become motivated to change their behavior positively (Eidhof & Harchaoui, 2017).

In this case, the municipality of The Hague is the payer. The investor will only be repaid if the predicted benefits are achieved and the quality of life – experienced by the members of the family – has remained the same or has improved. This intervention aims to decrease social costs by 20%. An independent organization monitors the reduction in social costs. No results have been published so far (Eidhof & Harchaoui, 2017).

2.2.2.2 Health Impact Bond

A more specific form of a SIB is a Health Impact Bond (HIB). A (private) investor is involved in this type of bond to finance healthcare interventions. If health benefits are achieved because of the implemented interventions, the investor receives (part of) his initial capital plus a fraction of the health benefits. This is done by agreeing on predefined performance indicators, with parties where the reduction in healthcare costs end up (health insurers, government, and municipalities). The goals are to improve the quality of care and to reduce healthcare costs. In this structure, it is also possible that payers reward the implementers not for their efforts, but actual results (Van Es et al., 2016). In order to clarify the usage of this financial instrument, three examples are given in the next paragraphs.

A HIB is deployed in Fresno, California, where the homes of children with asthma are preventively made dust-free. The expectation is that this will lead to a decrease in the number of hospital admissions. This intervention is expected to decrease healthcare costs. If an independent assessor confirms these reductions, the investment can be repaid with a small return (Clay, 2013).

Another HIB has been launched in Israel to prevent the development of type 2 diabetes. This HIB helps people with a high risk of type 2 diabetes to adjust their lifestyle. If these interventions are successful in preventing the development of diabetes, two Israeli health organizations and the National Insurance Institute will repay the investors with the savings made on healthcare costs (Moran, Moran & Fire, 2018).

In South Carolina, an initiative has been funded through a HIB to improve the quality of life for vulnerable mothers and their first babies. The lives are improved by creating Nurse-Family Partnerships, where nurses support mothers to improve prenatal health and prevent injury, abuse, and neglect of children. For the government, this leads to lower costs (Galloway, 2014).

Most prevention initiatives may have a measurable effect in the far future. For example, a campaign to stop people from smoking or a campaign to encourage people to brush their teeth will benefit society in the long term. However, these two examples cannot be funded using a HIB, because, in order to create a successful HIB, the effect of these interventions should be measurable within four years (Tummers, 2013).

However, the effect of the fall prevention programs on the number of injurious fall incidents and healthcare costs is expected to be measurable within a year. Therefore, when it is possible to assess the effect of fall prevention programs, and assuming that the programs reduce falls and healthcare costs, a HIB might be an applicable instrument to finance and implement these programs.

2.3 Knowledge Gaps

As was elucidated in section 2.2, the implementation of fall prevention programs is difficult due to a complex network of actors involved, insufficient national coordination, and financial barriers for local implementers. Moreover, the potential benefits of fall prevention programs are unknown as there is currently no method available to assess the effect of the programs on the number of injurious falls and

healthcare expenditures. However, these programs hold great promise to enhance the quality of life of older adults and to reduce healthcare costs.

When these programs have a measurable positive impact on the elderly population, it is essential to search for ways to encourage the implementation of fall prevention programs. One of these ways is to shift the financial risk from local entrepreneurs to investors by using a HIB. The HIB is a new financial instrument which has only been employed a few times for different healthcare interventions. Fall prevention programs have never been funded by such a structure even though these programs hold great promise and have the right characteristics for a HIB.

Thus, the following knowledge gaps have been identified:

1. A lack of insight in the effect of fall prevention programs on the number of injurious falls, the severity of fall incidents and the healthcare expenditures. Also, an evaluation method is lacking when the fall prevention programs are implemented in a municipality.
2. A lack of insight into the applicability of a HIB to encourage implementation of fall prevention programs.

2.4 Research scope and objective

In the literature review, it came to light that both topics (fall prevention programs and HIB) hold great promise to aid in reducing the number of injurious fall incidents and to improve the quality of life of older adults.

This study will go beyond these promises and aims to develop a method to determine the effect of fall prevention programs on the number of injurious fall incidents and healthcare expenditures of community-dwelling elderly. With this method, the economic feasibility of a HIB for fall prevention programs can be assessed. Other barriers for setting up these programs using a HIB regarding governance and law will be explored.

The evaluation method will not be designed to evaluate other interventions – like systematic home hazard assessment – that help to reduce fall incidents. Furthermore, the evaluation method considers only injurious falls for which (emergency) medical treatment is needed (hereafter: injurious fall incidents). A case study will be done to evaluate the method and to determine the impact of the programs.

2.5 Research question

The problem statement, literature review, knowledge gaps, and research objective lead to the following main research question:

“How can the effect of fall prevention programs on the number of injurious fall incidents and healthcare costs of community-dwelling elderly be determined in order to explore the applicability of a Health Impact Bond?”

In order to answer the main research question, the research can be divided into three sub-questions:

1. How can the effect of fall prevention programs be determined?
 - a. What are the types of injuries associated with falls in the elderly?
 - b. What are the treatment costs after an injurious fall per injury?
 - c. What are the total healthcare costs of an injurious fall?
 - d. What method can be used to assess the impact of fall prevention programs?

2. What is the impact of fall prevention programs on the number of injurious falls and healthcare expenditures of the elderly population?
3. Could a Health Impact Bond be an applicable instrument to aid in the implementation of fall prevention programs?
 - a. Does the reduction in healthcare costs, due to the implementation of fall prevention programs, exceed the implementation- and operational costs?
 - b. What are possible barriers regarding governance and law?

2.6 Scientific and societal relevance

2.6.1 Scientific relevance

By analyzing patient-specific hospital data, this study has a unique opportunity to assess the effect of fall prevention programs on the hospital expenditures of the elderly population of a specific area. In the current situation, there is no method available to determine the actual effect of fall prevention programs and RTCs are infeasible when these programs have been implemented on a large scale. Therefore, the opportunity is explored to evaluate the effect of the programs on the entire elderly population in an area using the Difference-in-Differences (DID) method.

A python model will be developed including the DID method and a clear explanation of the data preparation- and processing steps. This way, the research is easily replicable by anyone with a basic understanding of data analysis. In order to improve the method to assess the effect of fall prevention programs, this python model (including the DID method) could be used and improved in the coming years by researchers doing other case studies in other regions.

Furthermore, this study provides insight in how the innovative financing instrument HIB can contribute to aid in the implementation of fall prevention programs and elucidates on the barriers that need to be surmounted in order to make this instrument applicable.

2.6.2 Societal relevance and policy implications

Investigating the possibilities of a HIB and the effect of fall prevention programs on the healthcare expenditures, will help national safety institutes, such as VeiligheidNL, to stimulate initiatives to set up fall prevention programs. If the HIB would be applicable and beneficial for all parties involved, it might attract investors to partake in HIBs in regions across the Netherlands. Assuming that there is an actual effect, this might contribute to the Dutch efforts to lower healthcare costs of the elderly population and to increase their quality of life. Thus, this study might have an (indirect) effect on the individual older adult as well as the society as a whole.

On a national level, this research can provide valuable insights to be used in the discussion to control healthcare spending in the rapidly aging Dutch society. An example of such efforts is the yearly event ‘Landelijk Valsymposium’ (National fall symposium), which is organized by VeiligheidNL. During this event, national and international speakers present their recent research results on various topics to prevent fall incidents among older adults (VeiligheidNL, 2018). The method to measure the effect of the fall prevention programs (developed during this investigation) on the healthcare expenditures and number of injurious falls, and the insights about the possibilities of a Health Impact Bond, feed into this large national ongoing discussion.

On a local level, the results of the case study (introduced in chapter 3) will help local implementers of the fall prevention programs in the negotiations with the health-insurer to get funding to implement fall prevention programs in physiotherapy clinics in the surrounding areas (Hendriks, interview, 2019). Moreover, the effectiveness analysis can be redone to analyze the effect of the programs of this specific case in the years to come.

2.7 Report outline

Chapter 3 – 6 focuses on the main subject of the thesis: to assess the effect of fall prevention programs based on a case study. Chapter 3 introduces this case study and chapter 4 elaborates on the methodology of the analysis. Chapter 5 elaborates on the research methods and data processing. The results of this case study are shown in chapter 6.

Based on these results (chapter 6) and expert interviews (summarized in Appendix A), the applicability of a Health Impact Bond will be evaluated in chapter 7. In chapter 8, the conclusion of this investigation is given. Finally, chapter 9 discusses the results and reflects back on the research and the process. In the last paragraphs of this last chapter, recommendations for further research are given.

3

Introduction of the case study

The entrepreneur Arno Hendriks (owner of a physiotherapy clinic) managed to develop and implement the first fall prevention programs in eleven physiotherapy clinics in the eastern part of Dordrecht (Hendriks, interview, 2019). In this case study, the effectiveness of these programs will be assessed by analyzing patient-specific data of the Albert Schweitzer Hospital (ASZ). The method to determine the effectiveness will be described in chapter 4, and in chapter 5, more information can be found on the contents of the hospital dataset.

In this chapter, the case study is introduced by providing background information. The implementation areas are described in 3.1. In 3.2, the timeline of implementation is given. In section 3.3, the success factors for implementing and running fall prevention programs are elucidated. The current actor-network and funding structure is explained in paragraph 3.4. Finally, the costs- and income from the fall prevention programs implemented in Dordrecht-East are described in section 3.5.

3.1 Implementation areas

The fall prevention program 'Vallen Verleden Tijd' (Falling is past time) was implemented in eleven physiotherapy clinics in the following neighborhoods in March 2017: Sterrenburg, Stadspolders, Crabbehof, and Dubbeldam. In this thesis, these neighborhoods are considered to be in the region Dordrecht-East. The physiotherapy clinics work together under the name FysioDordt and the name of this operation is Drechtmix. Plans have been made to include more physiotherapy clinics in the rest of Dordrecht in the coming years (Drechtmix, 2017). The blue icons in the map below show the locations of the participating physiotherapy clinics and the red icon depicts the ASZ.

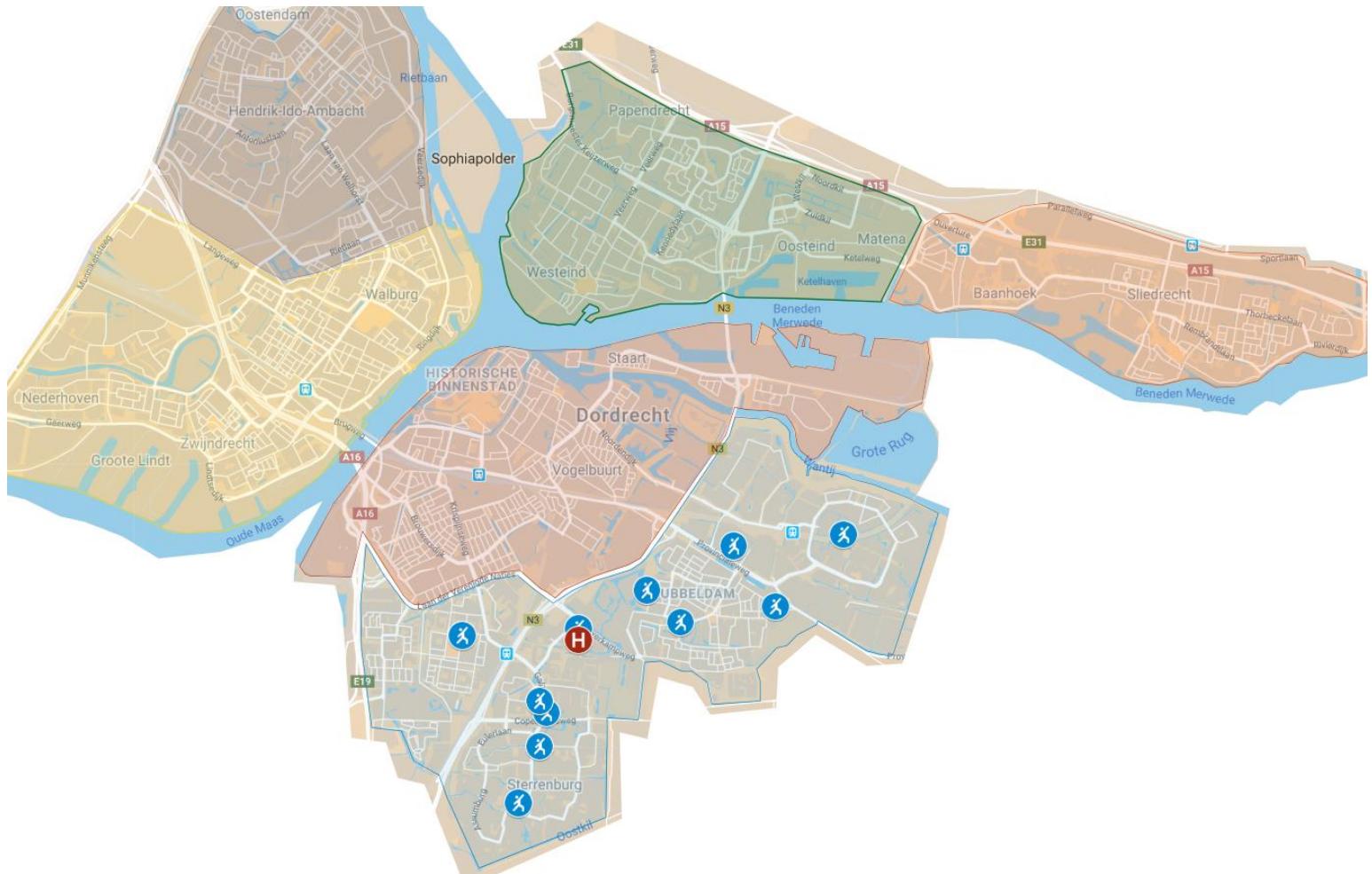


Figure 3: Areas where fall prevention programs have been implemented

In an interview with Arno Hendriks, it came to light that elderly are unable to – or are unwilling to – travel far distances to participate in a fall prevention project. This explains why, the participants of the fall prevention program all live in the blue shaded area (Hendriks, interview, 2019).

The service area of the ASZ is quite extensive. The closest hospital to the north is the Erasmus MC hospital in Rotterdam. In the south, the closest hospitals are the Amphia hospitals in Breda and Oosterhout, and to the east, the Beatrix Hospital in Gorinchem is closest. Small emergency departments have been established in Zwijndrecht and Papendrecht, but only minor injuries to (young) adults or children are treated in these facilities (Van der Velden, interview 2, 2019). In an interview with Emergency physician Annemarie van der Velden, it was confirmed that the vast majority of the elderly population living in Dordrecht-West, Papendrecht, Sliedrecht, Zwijndrecht, and Hendrik-Ido-Ambacht go to the Emergency Department of the ASZ after a fall incident (Van der Velden, interview 1, 2019). These regions are depicted in figure 3 as red, green, orange, yellow, and brown shaded areas, respectively. In chapter 5, more information is provided on these areas and their use in the effectiveness analysis.

3.2 Timeline of the Drechtmax project

In figure 4, the timeline of the entire Drechtmax project is shown.

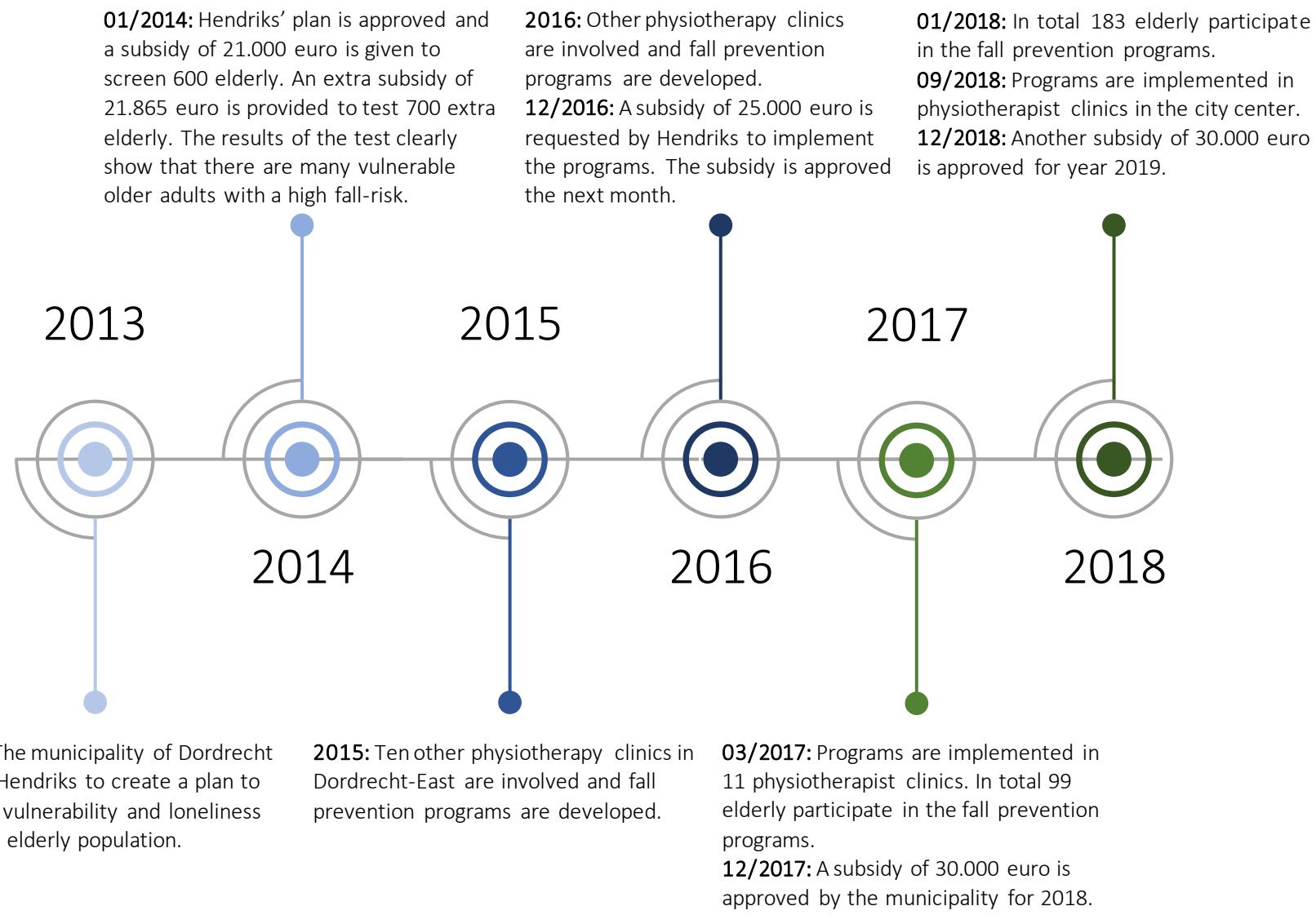


Figure 4: Timeline of Drechtmax project

By reviewing this timeline, it is striking to see that it was not easy for Hendriks to get the subsidy from the municipality even though the results of the screening-test clearly showed that a significant part of the elderly population was vulnerable and (extremely) lonely. It took him three years to convince the municipality of the importance of the programs, to develop the programs, and to persuade other physiotherapists in the area to partake in this endeavor. The 25.000 euros was just enough to implement and run the first fall prevention programs in 2017. The screening tests took longer than expected and he was not fully compensated for these extra invested working hours (Hendriks, interview, 2019).

3.3 Success factors for implementing fall prevention programs

The impact of these interventions depend on several factors. According to physiotherapist Arno Hendriks, three crucial aspects play a role in the effectiveness of a fall prevention program (Hendriks, interview, 2019):

1. The target group is reached (elderly with an increased risk of falling).
2. Effective interventions are deployed.
3. Well-organized cooperation is facilitated.

This section describes what is needed to ensure these aspects.

3.3.1 Reaching the target group

3.3.1.1 Case finding and screening for fall risks

For effective fall prevention, it is essential to choose – and specify – the right target group to set up a focused approach. Fall prevention programs are aimed at eliminating risk factors for falls and are therefore particularly useful if they are used for older adults with an increased risk of falling (Federatie Medisch Specialisten, 2018). This risk is easy to estimate based on a few predictors. The first predictor is someone's fall history. Secondly, it is relevant to check whether an older person has difficulty moving, walking, and maintaining balance. Another predictor is 'fear of falling' (Hendriks, Van der Velden, Van Houten, Verdenius, Logghe, Michielse, & Meinardi, multidisciplinary meeting 2, 2019).

Based on these predictors, the elderly – or their caregivers – can determine the fall risk. Nevertheless, case-finding is pre-eminently a task for first-line professionals who work with older adults or a social neighborhood team. It is best for them to determine whether a more extensive screening for fall risk is required. This screening includes a comprehensive assessment of individual risk factors, which makes it possible to advise an older person to take part in fall prevention programs. There are several options available for such screening tests, which include instruments such as the 'Fall-analyses' of Veiligheid NL (2017) and existing guidelines for fall prevention: the 'Directive on the prevention of fall incidents at elderly people' (Federatie Medisch Specialisten, 2018).

3.3.1.2 Motivating older adults

An impeding factor is that older adults usually see the benefit of prevention after a fall incident has occurred. Moreover, there is often no contact between elderly and professionals or organizations that provide fall prevention. Therefore, many older adults do not know their options to decrease their fall-risk (Hendriks et al., multidisciplinary meeting 1, 2018). The other way around also applies: performers of fall prevention programs only undertake action if an older person has already fallen. There is increased support for a new policy to check all adults over 65 annually to find out whether they have an increased fall risk. With this 'fixed' screening, elderly do not only get insight in their fall risk, but this new policy might contribute to a positive attitude towards fall prevention and might motivate them to take action in order to prevent a fall (Harchaoui et al., 2016). Nowadays, only elderly with a very high risk of falling participate in the programs as these older adults are recommended to participate in a program after a hospitalization (due to a fall). During an orientation day at the Emergency Department (ED) of the ASZ, many older adults, who were hospitalized due to a fall, admitted that they fell several times a month (Bink & Wingelaar, orientation day, 2019). Needless to say, these individuals have a very high risk of fractures.

It is also essential that older adults know what it means to take part in a fall prevention program and where they can follow such a program. It is not enough to only inform the elderly: listening to the wishes and needs of older adults is essential (Hendriks et al., multidisciplinary meeting 2, 2019). Various factors play a role in motivating. The tone in communication is important, because many older adults have low risk-awareness and older adults are often too stubborn to believe that they are likely to get injured as a result of a fall incident. The elderly dislike to talk about ‘getting old’ and everything related to that subject. According to Saskia Kloet (Kloet, interview, 2019), even the term ‘fall prevention’ does not appeal to older adults and does not attract the right attention. Concepts such as ‘Stay vital’ have proven to be more appealing. Providing the right information and using the right means of communication is essential to motivate older adults to participate. Family, friends, or even members from the Bridge club, the church-community or other elderly organizations, play a key role in providing information about fall prevention programs (Kloet, interview, 2019).

3.3.2 Effective interventions are deployed

As discussed in paragraph 2.2.1, multiple factors often play a role in fall incidents: mobility, the use of medication, fear of falling, vitamin D deficiency, bad vision, and environmental factors. A fall prevention program preferably has a multifactorial approach, including multiple interventions to affect all these factors (Hendriks et al., multidisciplinary meeting 1, 2018). This study focuses only on fall prevention programs that increase mobility, muscle strengthening, and decreases fear of falling. The promising program ‘Vallen Verleden Tijd’ or Nijmegen Falls Prevention Program (NFPP) has been implemented in Dordrecht-East. NFPP is a 10-week course consisting of several balance exercises and focuses on teaching an older adult how to act in the event of a fall (RIVM, 2017).

3.3.3 Well-organized cooperation

In Dordrecht, the fall prevention programs are well-organized and actors work closely together in order to provide a high-quality course. It is essential that there is a multi-disciplinary team with different professionals involved when implementing and running fall prevention programs. The operating parties must agree on quality requirements. For example, a quality requirement could be that the executors of the programs (in this case: physiotherapist) must have followed a training before they are authorized to run the program (Hendriks, interview, 2019).

According to Physiotherapist Hendriks, the best way to organize these fall prevention programs is to make sure that one party coordinates the organization and implementation. However, independence of the several participating physiotherapist clinics is relevant too. In this case, Hendriks played two roles: the organizer and executor of the programs (Hendriks et al., multidisciplinary meeting 2, 2019). The municipality has a clear responsibility to organize public health under the Public Health Act, which includes prevention. The management of the project will be done by the local implementer (organizer), but the municipality can help to connect the various actors needed to implement fall prevention programs (Harchaoui et al., 2016). In the next section, the dependencies of the actors involved as well as the current funding structure are described.

3.4 Current actor-network and funding structure

This section describes the actor-network involved in facilitating the fall prevention projects in Dordrecht-East and provides insight into the current funding structure.

3.4.1 Healthcare Acts in the Dutch system

Three healthcare acts in the Dutch healthcare system are relevant in elderly care. The Health Insurance Act (Zorgverzekeringswet, Zvw) is accountable for the bulk of the healthcare budget. Every person in the Netherlands is legally obliged to have standard health insurance to cover the costs of, for example, hospital treatment or the costs of a consult given by the general practitioner. This act is governed by

private health-insurers and healthcare providers. The health insurance companies compete with one another, but are not-for-profit corporations that allocate any profits they make to the reserves they are required to maintain or return them for lower premiums (Ministerie van Volksgezondheid, Welzijn en Sport, 2016).

If a person is living in the Netherlands, he or she is insured for long-term care through the Long-Term Care Act (Wet Langdurige Zorg, WLZ). This is general insurance for individuals with long-term care needs that stay in an institution or at home. Mostly frail elderly and people with severe disabilities or chronic illness make use of the WLZ. The WLZ is governed by care offices (ZonMW, 2017).

Municipalities are responsible for local forms of care and aim to encourage initiatives that improve the health of the local population. The Social Support Act provides for this kind of support (Wet Maatschappelijke Ondersteuning, WMO). The subsidies given to mister Hendriks to develop and implement the fall prevention programs, are provided through the WMO (Ministerie van Volksgezondheid, Welzijn en Sport, 2016).

This research focuses on the possible cost reduction within all three healthcare-related acts as older adults often make use of a combination of the Acts.

3.4.2 Actor-network involved in fall prevention programs

There is a complex actor-network involved in fall prevention programs. In the figure below, a simplified version of this actor network is shown to illustrate the current financing structure and the actors involved.

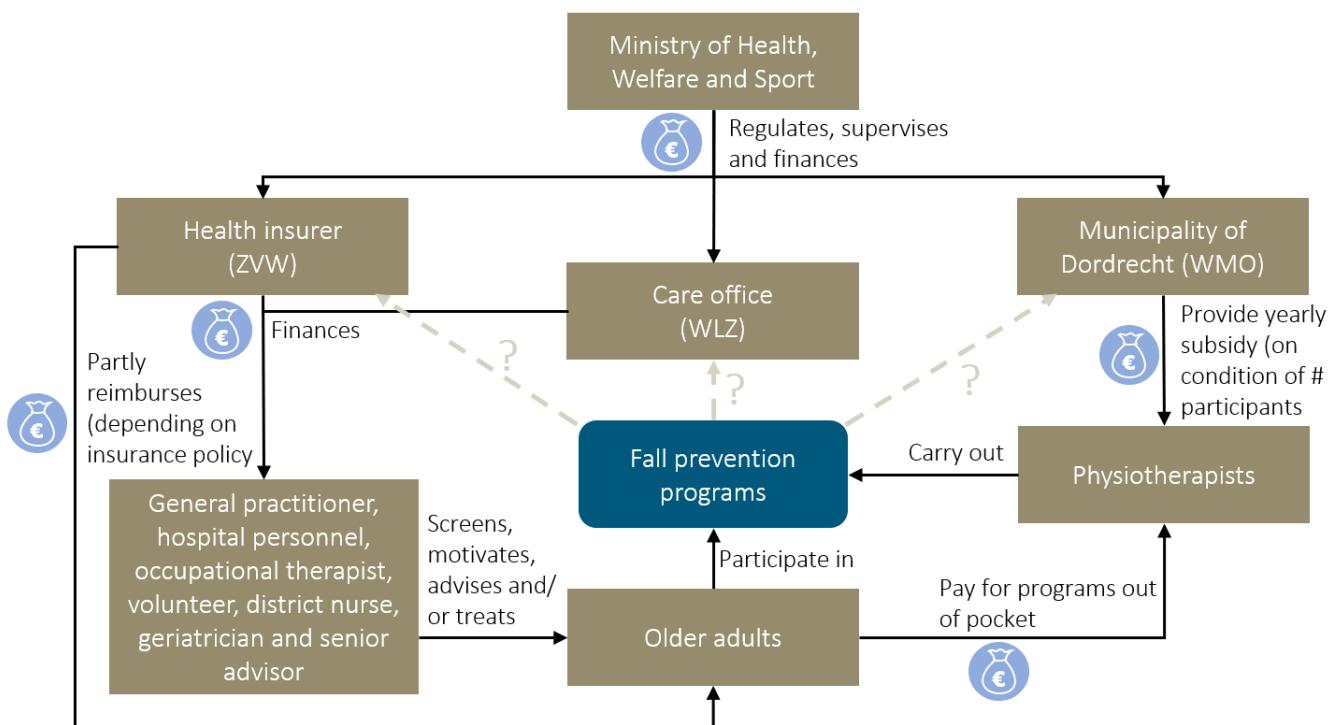


Figure 5: Current funding structure and actor-network

The Ministry of Health, Welfare and Sport (VWS) regulates, supervises, and finances the three healthcare Acts governed by the health insurer, care offices, and municipalities. The health insurer and the care office provide funding for the activities done by the general practitioners, hospital personnel, occupational therapists, volunteers, district nurses, geriatricians, and senior advisors. The health insurer also partly reimburses older adults for participating in fall prevention programs, but the amount of compensation depends on the insurance policy of the older adult. The general practitioners, hospital personnel, occupational therapists, volunteers, district nurses, geriatricians, and senior advisors screen, motivate and advise the older adults. In case of an injurious fall, the older adults receive the necessary care from these same actors (Hendriks et al., multidisciplinary meeting 1, 2019).

Physiotherapists (and local implementers) receive a yearly subsidy from the municipality of Dordrecht on the condition that a certain number of participants is reached and that they receive positive outcomes on a questionnaire. The physiotherapists carry out the fall prevention programs and receive out-of-pocket cashflow from older adults to cover the rest of the costs (Hendriks et al., multidisciplinary meeting 1, 2018; Bink & Wingelaar, orientation day, 2019; Hendriks, interview, 2019).

As described in chapter 2, the fall prevention programs hold great promise to affect the costs of the insurer, the care offices, and the municipality. Currently, this effect is unknown. Therefore, an evaluation method is developed during this investigation to determine this effect.

3.4.3 Issues that arise from the complex network of actors involved

As mentioned in section 3.2, getting a subsidy to implement and carry out fall prevention programs takes several years. Because of this and the fact that the programs are not structurally financed, parties are less likely to join such a multidisciplinary partnership. According to Saskia Kloet of VeiligheidNL, several other small prevention initiatives in other municipalities in the Netherlands ended as soon as financing (subsidy) ended (Kloet, interview, 2019).

Another issue is that, due to the complex network of actors, it is hard to connect all the stakeholders to align the incentives and to improve cooperation (Kloet, interview, 2019). The importance of cooperation between stakeholders became apparent after two open days at the hospital. Some of the nurses and physicians at the Emergency Department (ED) were not even aware of the fact that these fall prevention programs were implemented (Bink & Wingelaar, orientation day, 2019). Moreover, the hospital personnel that was aware of these programs had another issue: they were not authorized to pass down contact details of an elderly to a physiotherapist clinic that offers these programs due to privacy issues. Currently, a multidisciplinary team tries to set up a system that enables physicians and nurses to get contact details of the elderly in the last consult after a fall incident at the ED. This would enable physiotherapists to contact these vulnerable older adults to offer them a fall prevention program (Hendriks et al., multidisciplinary meeting 2, 2019).

3.5 Costs- and income from fall prevention programs

3.5.1 Cost of fall prevention programs in the current situation

Physiotherapist Arno Hendriks (Hendriks, interview, 2019), provided information about the number of participants of the fall prevention programs as well as information about the implementation- and operational costs. The total costs of implementation and performing the programs (between March 2017 and September 2018) are depicted in the waterfall chart below.

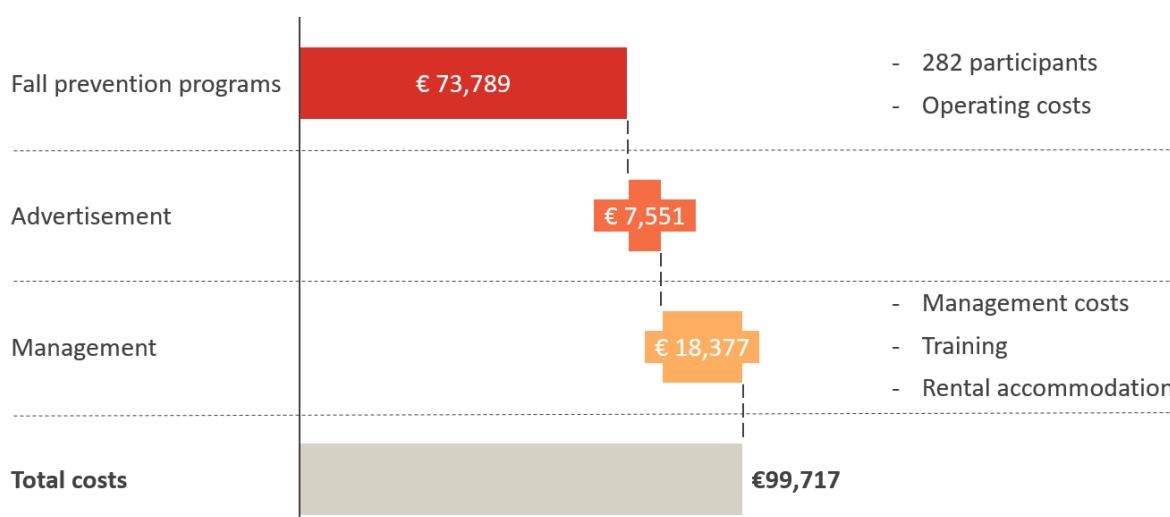


Figure 6: Operational costs of fall prevention programs 2017-2018

The costs depicted in figure 6 only include operational costs to provide the fall prevention program to 282 participants in Dordrecht-East. As depicted in the timeline (figure 4), costs were also made to screen 1.300 elderly and to develop the fall prevention programs. The total expenditures of this starting phase (screening elderly and developing programs) were €42.865, which were fully covered by two subsidies provided by the municipality (Hendriks, interview, 2019).

This data will be used in chapter 7 to determine whether the (possible) reduction in hospital expenditures outweigh the costs of the programs.

3.5.2 Income from fall prevention programs in the current situation

In figure 7, the income from the fall prevention programs of the first year of implementation are illustrated (Hendriks, interview, 2019). The subsidy provides over half of the income required to cover the operational costs. The other costs are covered by the older adults themselves (partly out-of-pocket and partly reimbursed by the health insurer).

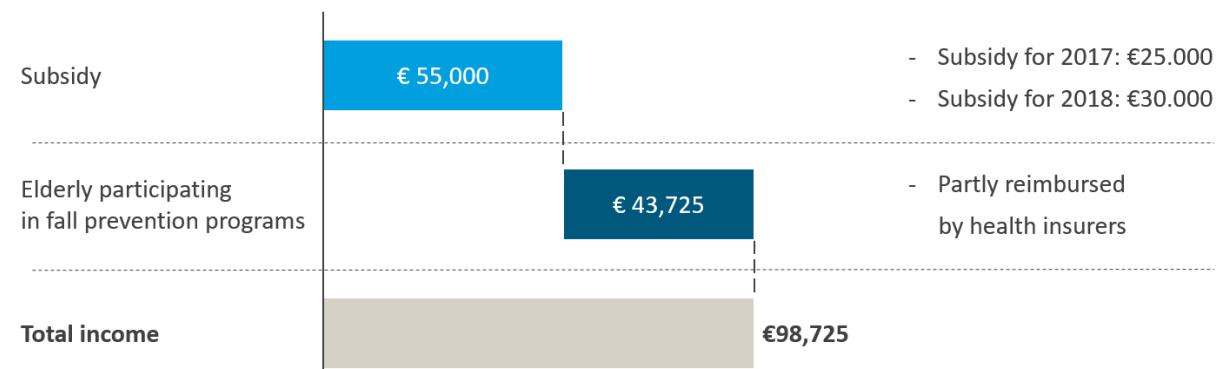


Figure 7: Income from fall prevention programs 2017-2018

3.5.3 Current financial barriers

As illustrated in figure 7, the participating out-of-pocket costs are essential for the continuation of fall prevention programs. However, this means that there is a financial barrier for older adults to participate. There is also a substantial barrier for the local implementer as the subsidy was not sufficient in this first year of implementation to cover all the costs: the entrepreneur Arno Hendriks was forced to lower the management costs in order to continue with the project. Also, it takes a long time to convince the municipality of the relevance of fall prevention programs in order to get a subsidy (Hendriks, interview, 2019).

Because of privacy issues, there is no way to track the healthcare history of older adults as hospitals cannot provide details of the healthcare history of older adults. Currently, there is no method to evaluate the effect of fall prevention programs (Kloet, interview, 2019).

Structural resources are needed to implement fall prevention programs: for reaching and motivating the elderly, for the reimbursement of (extra) activities by parties, and for financing the organizational costs to set up and manage the program. A HIB could deliver these resources, provided that there is a right balance between costs and benefits. If financing can be guaranteed via a HIB by a private party, the burden of proof can be shifted from the local implementer to the investor. Chapter 7 will elaborate more on this topic.

4

Methodology

This study focuses on developing an evaluation model to assess the effect of the fall prevention programs on the population of an entire region. There are enough participants (282) and these older adults all come from Dordrecht-East. In addition, it came to light during an orientation day at the ED of the ASZ, that many older adults, who were hospitalized due to a fall, admitted that they fell several times a month (Bink & Wingelaar, orientation day, 2019). Needless to say, these individuals have a very high risk to be hospitalized due to a fall. These fragile elderly are often the ones participating in these programs (Hendriks, interview, 2019). By providing a fall prevention program for these older adults, the fall risk can be decreased tremendously (Kloet, interview, 2019). Therefore, an effect on the population of the region Dordrecht-East might be visible when analyzing the hospital data. The methodology to evaluate this data to determine the effect of the programs is described in this chapter.

This study explores the possibility to use the Difference-in-Differences (DID) method to determine the effect of the fall prevention programs on the number of injurious falls and hospital expenditures. With this method, the effect of the programs can be estimated by comparing hospital data of the elderly population in the intervention area (Dordrecht-East) before and after the implementation of the programs as well as comparing hospital data before and after the intervention of a population that has not been exposed to the treatment (control group). Medical data and several other datasets have been collected in order to conduct this analysis.

In section 4.1, the DID method will be explained and in section 4.2, the DID estimate equation and (WLS) regression method will be described. Finally, the method to determine the effect of the fall prevention programs on the total healthcare expenditures, will be elucidated in section 4.3.

4.1 Difference-in-Differences method

4.1.1 Introduction to the DID method

The DID design is a quasi-experimental research design that researchers often use to study the effect of policy interventions where RCTs are infeasible. DID is not a perfect substitute for randomized experiments, but it often represents a way to learn about causal relationships. The goal of a DID analysis is to find the unbiased effect of a policy or treatment using observational data without running an experiment (Hayashi, Kondo, Suzuki, Yamada, & Matsumoto, 2014).

The first difference-in-differences project was done in the 1850s by Dr. John Snow in England to show that the disease cholera came from drinking contaminated water. In London, water was supplied by two companies, both of which initially drew it right out of the Thames. Raw sewage was dumped in this highly populated area and, as a result, the water was contaminated. However, in 1852, one of the companies started sourcing their water from a spot upstream from London. The researcher compared death rates in districts served by the two water companies before and after the one company started using cleaning water. He found that cleaner water considerably lowered mortality from Cholera (Snow, 1855).

DID is designed to control for any possible factors, both observable and unobservable that are constant over time. The basic idea is to have two groups: one that receives the treatment or is affected by the policy under study, and another group that is not affected. Another requirement is to have data before and after the treatment occurs. The DID method calculates the difference in outcomes between the two groups before treatment and the difference in groups after treatment. The difference between those two differences is the estimated effect of the treatment or policy (Stock & Watson, 2003).

By only using the change in the difference between the treatment- and control groups to measure the effect of treatment, the time-invariant factors are removed that might be associated with both the selection of the treatment and the outcome of the treatment. This is true for both the observable and unobservable factors (Bertrand, Duflo & Mullainathan, 2004). The concept of the method is visualized in the following figure:

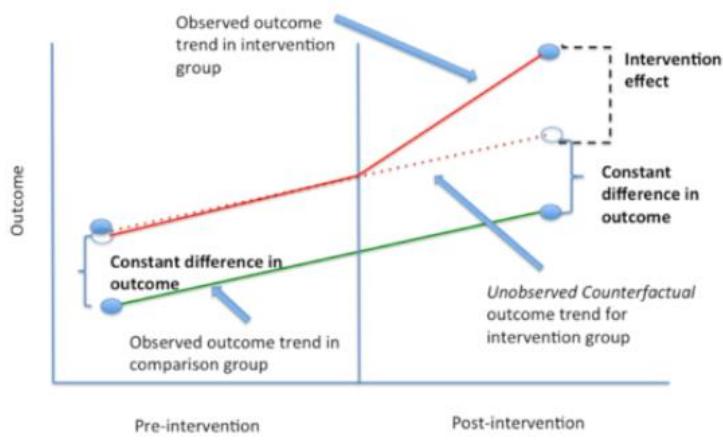


Figure 8: The concept of a difference in difference method (Branas et al., 2011)

4.1.2 The difference between the DID method and a RCT

The DID and RCT method both include a study population, with a control- and intervention group and a set of treatment conditions. The most important difference is that the treatment conditions are not randomly assigned across units in a DID. In an RCT, the conditions are randomly assigned and, the treatment exposure is statistically independent of any factor that might also affect outcomes (Wing, Simon & Bello-Gomez, 2018). DID assumes that confounders varying across the groups are time-invariant, and time-varying confounders are group-invariant. In other words, DID relies on the assumption that the unobserved differences between treatment and the control groups are the same over time when the intervention would not have taken place. This is regarded as the Common Trend Assumption (CTA) (Branas et al., 2011).

4.2 DID-estimating equation and WLS regression

4.2.1 Difference-in-Differences estimating equation

There are two groups ($g = 1,2$) observed in four time periods ($t = 0,1,2,3$) in this DID design. In the third period, only the second group is exposed to the treatment condition. In this case, the $g=1$ is the control group, and $g=2$ is the intervention group. Let $I_g = 1$ (where the group is $g=2$) be a dummy variable indicating observations on the intervention group. I_g has no time subscript as group membership does not change over time. In section 5.2, the exact neighborhoods in the intervention- and the control group will be determined. In the case under study, this variable is equal to 1 for the zip codes (4 digits) in the region Dordrecht-East and 0 for the zip codes in the regions not affected by the intervention.

In this case study, t_0 stands for year 2014-2015, t_1 for the year 2015-2016, t_2 for year 2016-2017 and t_3 for the year 2017-2018. The dummy variable $P_{1t} = 1$ (where the time period is t_1) and 0 in any other period. Dummy variable $P_{2t} = 1$ where the time period is t_2 and variable $P_{3t} = 1$ where the year is t_3 . The variable P_{3t} indicates observations from the post-intervention period (2017-2018).

The treatment variable is the product of I_g and $P3_t$. This dummy variable is 1 only for when an observation is both in the intervention group and in the post-period 2017-2018.

The DID-estimating equation will be used twice to determine the effect of the programs on two (dependent) variables: the number of fall incidents per 100 elderly and the total average hospital costs per elderly. The outcome variable Y_{gt} represents either the number of fall incidents per 100 elderly or the total average hospital costs per elderly, in period t in group g . ϵ_{gt} is the error term. The Difference-in-Differences effect can be estimated with the following estimating equation:

$$Y_{gt} = x_0 + x_1 I_g + x_2 P1_t + x_3 P2_t + x_4 P3_t + x_5 (I_g * P3_t) + \epsilon_{gt} \quad (4.1)$$

The DID method calculates the difference in outcomes between the two groups before treatment and the difference in groups after treatment. The difference between those two differences is the estimated effect of the treatment or policy. The coefficient x_5 provides this Difference-in-Differences estimate, which is the average estimated treatment effect.

As mentioned before, this method can only be used when the CTA holds. This assumption holds if in the absence of the treatment, the average outcomes for treated and control groups have followed parallel trends over time. In other words, when the number of injurious falls per 100 elderly increases in the control group in a pre-intervention year, the number of injurious falls per 100 elderly should also increase in the intervention group in that same year. In section 4.2.3, the method to test this assumption is described.

4.2.2 Weighted Least Squares regression

For this DID design, it is required to run a Weighted Least Squares (WLS) regression. WLS regression is used in analyses where there is evidence of heteroscedasticity errors that are associated with the least squares regression results. In this type of regression, weights are added to each case to adjust the contribution of those cases to the computation of the regression coefficients and the standard errors. This helps to get unbiased standard errors to test the significance of the regression coefficients (Stuart, Huskamp, Duckworth, Simmons, Song, Chernew & Barry, 2014).

In this case in Dordrecht, the WLS regression is used to make sure that the regions with a high elderly population contribute more to the regression coefficients than regions with a low elderly population. The required weights to run the WLS regression are the total number of elderly (per age group) living in each zip code area. The outcome coefficient of interest (x_5) will represent the weighted average estimated effect of the fall prevention programs on the number of fall incidents per 100 elderly and the total average hospital costs per elderly.

4.2.3 Using the DID method to test the CTA

The CTA assumption is tested by using the same DID method as described in 4.2.1. This time, however, the difference in outcomes between the control- and intervention group is checked in the pre-intervention years. The post-intervention data is excluded in this test. As the ASZ data contains data from 2014 until 2018, there are four full years available to examine (see section 5.3 for more detailed information about the ASZ dataset). Two analyses will be done to determine whether the CTA holds: checking the trend between year 2014-2015 and year 2015-2016 (equation 4.2, data excluded from 2016-2018), and year 2015-2016 and 2016-2017 (equation 4.3, data excluded from 2017-2018). The following estimation equations are used to do these two tests:

$$Y_{gt} = x_0 + x_1 I_g + x_2 P1_t + x_3 (I_g * P1_t) + \epsilon_{gt} \quad (4.2)$$

$$Y_{gt} = x_0 + x_1 I_g + x_2 P1_t + x_3 P2_t + x_4 (I_g * P2_t) + \epsilon_{gt} \quad (4.3)$$

The CTA holds when the coefficient of the DID estimate (in equation 4.2: x_3 and in equation 4.3: x_4) is close to 0 and the p-value is high.

4.3 Assessing the effect of the programs on the total healthcare costs

It is expected that a possible reduction in the number of fall incidents results in lower hospital expenditures per elderly. However, a possible reduction in falls does not only result in lower hospital expenditures funded through the Health Insurance Act (ZVV), but also in the Long-Term Care Act (WLZ) and the Social Support Act (WMO). The Dutch Consumer Safety Institute (VeiligheidNL) has estimated the average total healthcare costs of a fall incident per age group in the ZVV, WLZ, and WMO with data from their Injury Surveillance System (Letsel Informatie Systeem, LIS). The results of their analysis (VeiligheidNL, 2017) in combination with the results from the DID method (effect on the number of fall incidents) will be used to determine the effect of the programs on the total healthcare costs.

5

Research methods and data processing

5.1 Research framework

In order to conduct this research, a combination of qualitative- and quantitative research methods have been used. The research framework illustrates how these different research methods, research activities, and datasets contribute to the research in order to answer the main research question.

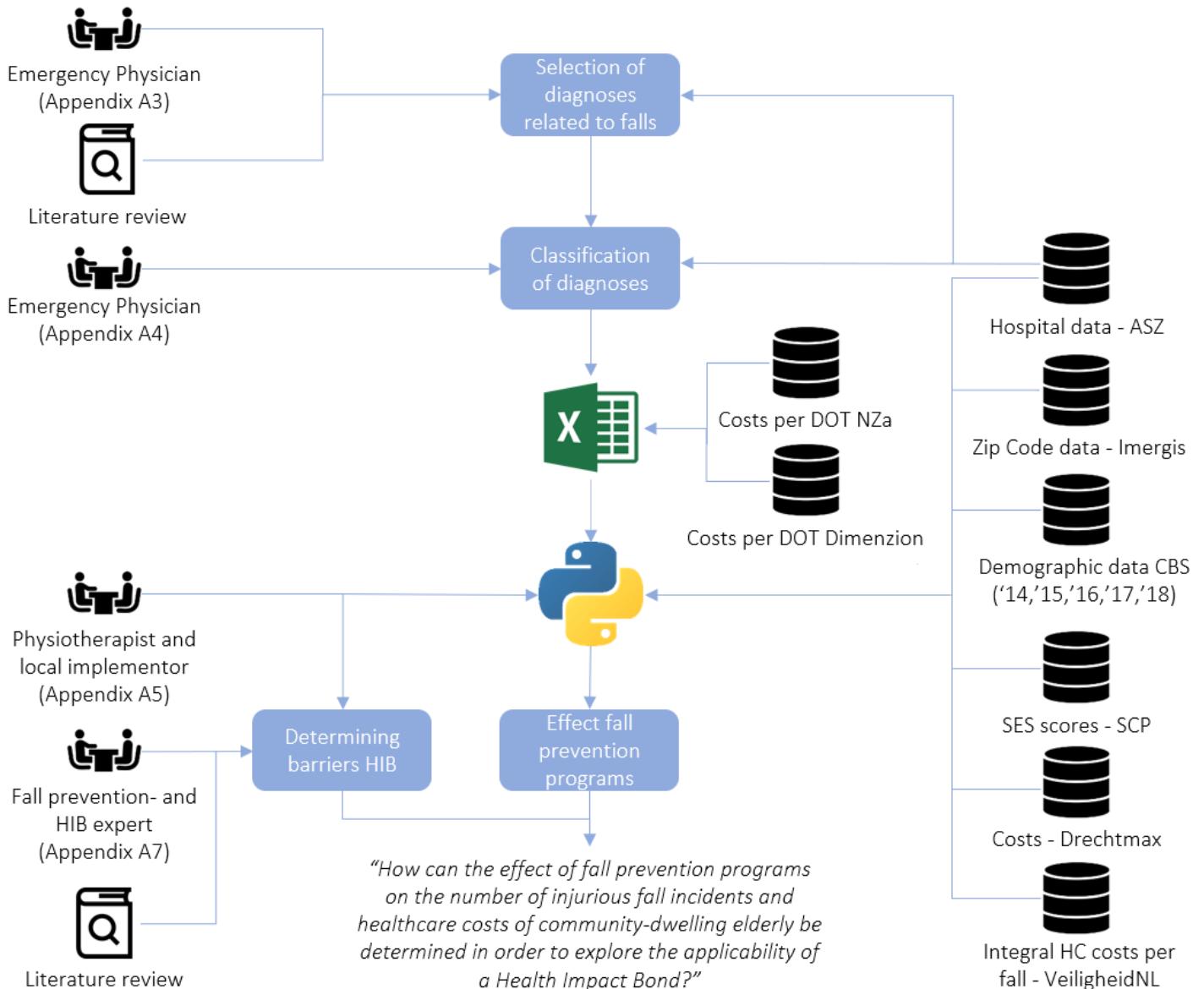


Figure 9: Research framework

By doing a literature review and two interviews with Emergency Physician Annemarie van der Velden (Van der Velden, interview 1, 2019; Van der Velden, interview 2, 2019), it was possible to select and classify the diagnoses related to fall incidents. All the diagnoses and diagnoses-treatment-combinations (DOTs) in the ASZ dataset were evaluated and the Excel 'Selection relevant diagnoses and classification' was created as a tool to discuss the different diagnoses and their severity with the Emergency Physician (Appendix F). A DOT is a diagnose treatment combination containing the whole course of treatment from the first consultation until the last contact with hospital personnel. The type of diagnosis and DOT depend on several characteristics, such as the severity of the (fall) injury and the condition of the patient. The average costs of these DOTs were determined based on two datasets from the Dutch Healthcare Authority (Nederlandse Zorgautoriteit, NZa) and the data in the Dimension database containing DOT-prices of the ASZ.

Anonymized patient-level hospital data from the ASZ was collected, which will be used as the primary dataset to assess the frequency, type, and costs of fall incidents in the neighborhoods around the hospital. The hospital dataset contains hospital discharge data of DOTs and other information of individual patients. Data about the costs and classification of the selected diagnosis and DOTs were combined with the hospital dataset in a python file, as well as five other databases, to create a model to determine the effect of the fall prevention programs.

In an interview, Physiotherapist Arno Hendriks (Hendriks, interview, 2019) provided information about the participants of the fall prevention programs as well as information about the implementation- and operational costs. An expert on fall prevention programs and HIBs, working at the Dutch Consumer Safety Institute, provided information about the possible law- and governance barriers when implementing programs using a HIB. The combination of the information from these interviews and the analysis of the effect of fall prevention programs, makes it possible to answer the main research question.

In section 5.2, the intervention- and control group are chosen based on a strategy to minimize selection bias. In section 5.3, more information will be provided on the fall-related diagnoses, the contents of the hospital dataset, the various other datasets used in the analysis, and data-preparation. This will contribute to a more thorough understanding of the ASZ dataset. In section 5.4, a table is shown containing the demographic data, number of falls, and total hospital expenditures per neighbourhood per year, which will be used in the analysis to determine the effect of fall prevention programs. Finally, section 5.5 elaborates on the reproducibility and replicability of the research.

5.2 Defining the control- and intervention group

When analyzing the effect of fall prevention programs using the DID method, most external factors influencing the outcomes are constant over time and are captured by the fixed effect. However, the DID design might be susceptible to selection bias: the population exposed to the treatment may be different from the individuals who are not exposed to the intervention. The control- and intervention group must be similar and must be exposed similarly to other factors (such as seasonal differences) that influence the outcomes to generate an unbiased estimation of the treatment effect. One of the ways to minimize selection bias is to choose a control group with similar characteristics as the intervention group (Stuart et al., 2014).

Two variables need to be reviewed to make sure that the two groups are similar: seasonal differences between the periods (section 5.2.1.1) and socioeconomic differences between districts (section 5.2.1.2) (Bink & Wingelaar, orientation day, 2019; Van der Velden, interview 1, 2019). In section 5.2.2, it is decided which areas are included in the dataset as the intervention- or control group.

5.2.1 Determining a strategy to minimize selection bias

5.2.1.1 Seasonal differences between periods

Emergency Physician van der Velden emphasized in an interview (Van der Velden, interview 1, 2019) that seasonal differences between periods affect the number of fall incidents. However, the seasonal differences are assumed to be time-varying factors that affect the regions identically. By only using the change in the difference between the treatment- and control groups to measure the effect of treatment (DID method), the seasonal differences will not affect the outcome if the common trend assumption holds.

5.2.1.2 Socioeconomic differences between neighborhoods

Hayashi et al. (2014) found out that socioeconomic differences between neighborhoods affect the number of fall incidents. In the Netherlands, the socioeconomic differences can be compared by looking at the socioeconomic status (SES) scores that are attributed to each zip code region by the Netherlands Institute for Social Research (SCP). This score indicates the social status of a neighborhood in comparison to other neighborhoods in the Netherlands and is based on the main household income, percentage of households with a low income, percentage of inhabitants without a paid job, and percentage of households with a low level of education (Sociaal- en Cultureel Planbureau, 2019).

In the Netherlands, there are considerable differences in health between people in regions with high- and low SES. For example, highly educated people (higher professional education or university education completed) live on average more than six years longer than lower educated people (only primary education). The poor health of individuals with a low SES is partly caused by their lifestyle and environment (Sociaal en Cultureel Planbureau, 2019).

In order to minimize selection bias, it is vital to take socioeconomic differences into account. Therefore, a control group with a similar SES as the intervention group should be selected. In the next paragraphs, the control- and the intervention group are determined based on these scores.

5.2.2 Determining the intervention- and control group

5.2.2.1 Determining the intervention group

As sufficient data has been collected, and a strategy has been chosen to minimize selection bias, a control- and intervention group can be defined which will be included in the dataset to analyze the effect of fall prevention programs using the DID method. The map of Dordrecht and other surrounding areas are depicted in the figure below to visualize the potential intervention- and control group areas.

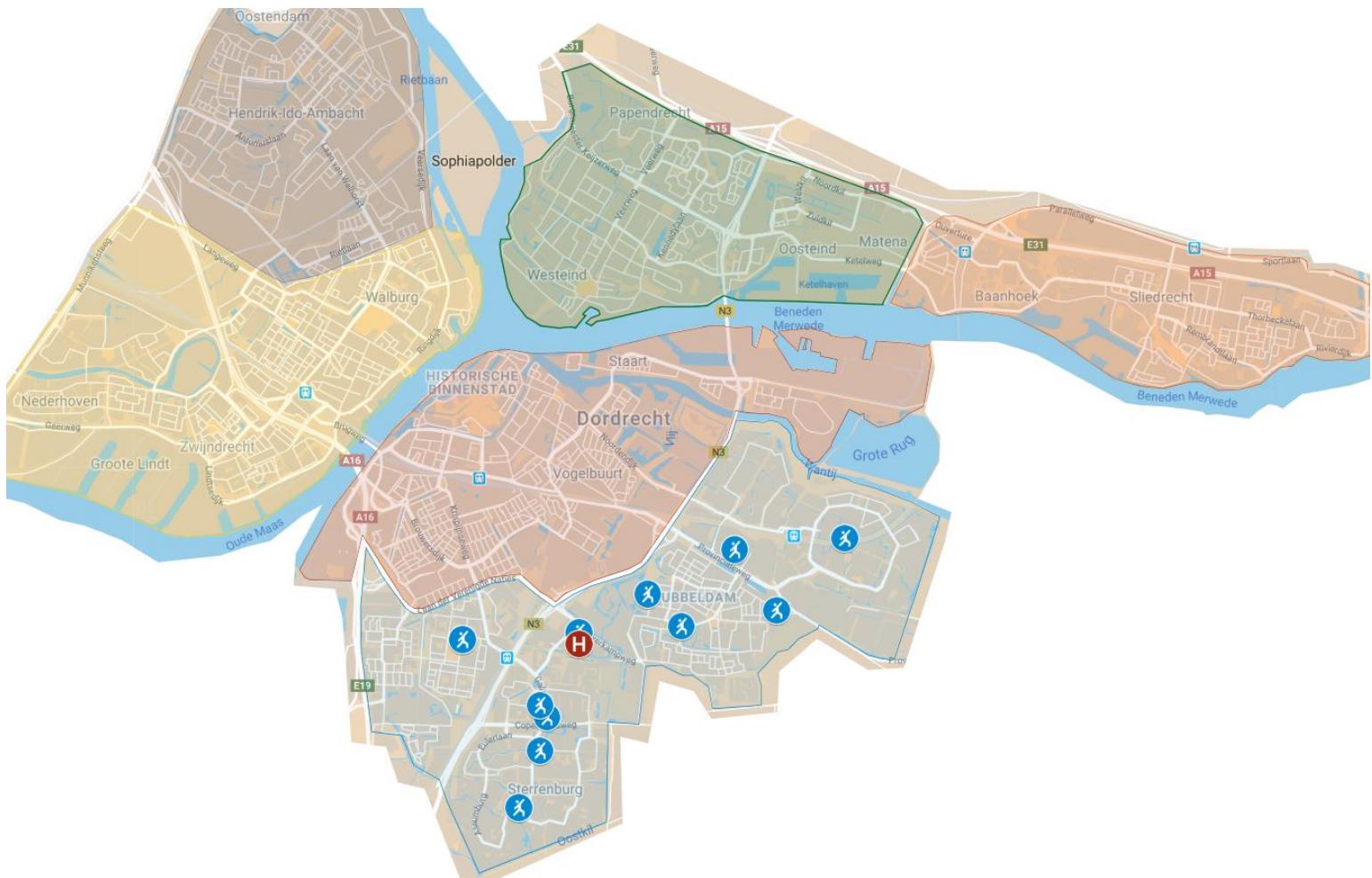


Figure 10: Map of Dordrecht and surrounding municipalities

The fall prevention programs have been implemented in eleven physiotherapist clinics in the east of Dordrecht in the neighborhoods Sterrenburg, Stadspolders, Crabbehof, and Dubbeldam. No other programs have been implemented in any other area in- or around Dordrecht (Hendriks, interview, 2019). Therefore, the elderly population in Dordrecht-East is the intervention group, which is indicated by the blue shaded area in figure 10.

5.2.2.2 Determining the control group

In an interview with Emergency Physician Annemarie van der Velden, it was confirmed that the vast majority of the elderly population in Dordrecht and the surrounding municipalities go to the Emergency Department of the ASZ (Van der Velden, interview 1, 2019). That means that the SES-score of several potential control groups can be compared to the SES-score of Dordrecht-East in order to minimize selection bias. The potential control group areas can be reviewed in figure 10.

In figure 11, the socioeconomic status of several areas in and around Dordrecht are compared to the SES-score of the intervention group: Dordrecht-East (Sociaal en Cultureel Planbureau, 2019). If the difference in SES-score between the intervention area and the (potential) control area is less than one, the elderly population in that area will be used as the control group. The following control areas will be compared to the intervention group: Dordrecht-West, Hendrik-Ido-Ambacht, Papendrecht, Zwijndrecht, and Sliedrecht.

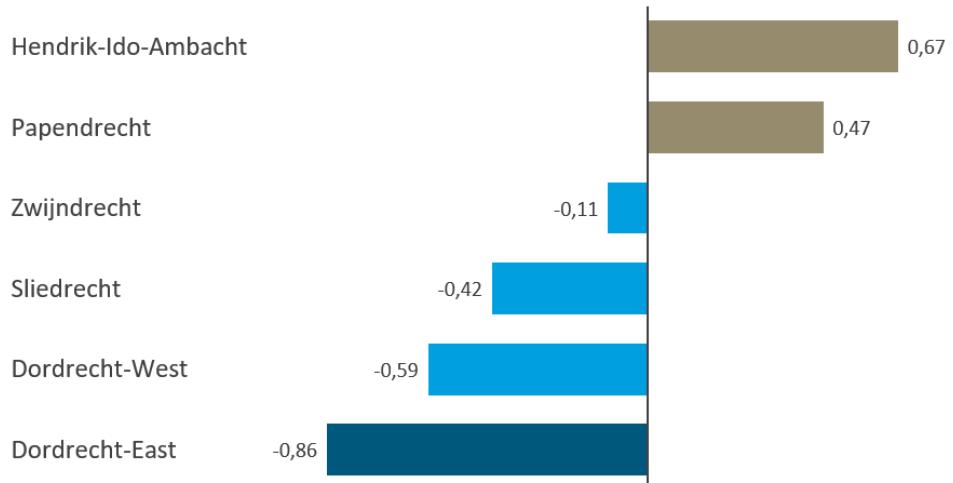


Figure 11: SES scores of Dordrecht and surrounding municipalities

Based on figure 11, the regions Dordrecht-West, Sliedrecht, and Zwijndrecht (figure 10: red, orange, and yellow) have been chosen as the control group. The SES-scores of these regions are closest to the SES-score of the intervention area Dordrecht-East. These areas will be included in the dataset.

5.3 General information about the contents of the datasets used

Section 5.3.1 describes the contents of the ASZ dataset and elaborates on the data-preparation. The types of diagnosis related to fall incidents are described in 5.3.2. To get a feeling of the data, and to emphasize the relevance of the problem of falls in the elderly, the total yearly costs per severity level in different age groups will be shown in 5.3.3. Finally, the total healthcare costs per fall, estimated by VeiligheidNL, will be illustrated in 5.3.4.

The outcomes of these general analyses of the data have been checked by Emergency Physician Annemarie van der Velden to validate the dataset (Van der Velden, interview 1, 2019; Van der Velden, interview 2, 2019).

5.3.1 Contents of the ASZ dataset and data preparation

A python model has been developed to prepare the ASZ dataset and to conduct the analysis described in chapter 4. The following data in the ASZ dataset is available:

- Patient number (anonymized)
- Age of patient (65+)
- Gender of patient
- DOT-code
- DOT-description
- Start date of DOT
- End date of DOT
- Diagnosis code
- Diagnosis description
- Specialism
- Zip code (to track the neighborhood of patient)

- Living situation (Nursing home or living independently)

As mentioned before, anonymized hospital data from 2014 until the end of 2018 is used for this analysis. The last three months of the year 2018 cannot be used as many DOTs were not closed at the time of collection and a lot of data was therefore missing. The fall prevention programs were implemented in March 2017, and the effect of the programs start about six months after the implementation date: in September 2017 (Hendriks, interview, 2019). The number of DOTs (related to fall incidents), before and after the intervention, will be subtracted from the ASZ dataset each year from September to September. The following years were subtracted from the dataset: 2014-2015, 2015-2016, 2016-2017, and 2017-2018.

This dataset has been enriched with the data from the excel file to add the severity level and costs per DOT. To get a feeling of the data, an example sample of the ASZ dataset is shown in table 1.

Table 1: Example sample of ASZ dataset

Patient number	Start date DBC	Zip code	Age	Living situation	Diagnose	DBC-Code	Severity	Cost of DOT	Region	Analysis year
1234567	3-feb-18	3315	83	Nursing home	Femur fracture	199299054	6	€9505	Dordrecht-East	2017-2018
7654321	5-feb-15	3311	69	At home	Contusion	199299	2	€445	Dordrecht-West	2014-2015

Table 1 shows details of two patients. The first patient came to the ED with a hip fracture (femur) in February 2018 and lives in a nursing home in a zip code area in Dordrecht-East. The cost of the femur DOT is €9505, and the fall incident occurred in the intervention area Dordrecht-East in the post-intervention period 2017-2018. However, as this study focusses on community-dwelling elderly, this fall incident will not be included in the analysis as this individual lives in a nursing home.

The second patient came to the ED after a fall with a contusion in February 2015 and lives at home in Dordrecht-West. The cost of the contusion DOT is €445, and the fall incident occurred in the control area Dordrecht-West in the pre-intervention period 2014-2015. This fall would be included in the final dataset as this older adult lives at home.

Demographic data is needed to determine the number of older adults per age group in each zip code region (Central Bureau of Statistics, 2017). By combining this CBS-data with the ASZ-data, it is possible to compute the number of injurious fall incidents per 100 elderly for each zip code region and compute the average hospital costs per elderly for each zip code region. In Appendix C, the demographic data per region and age group can be found. Also, this Appendix contains details of the number of elderly living in a nursing home per age group (Central Bureau of Statistics, 2018). The number of community-dwelling elderly in each zip code region is used in the analysis to determine the effect of the fall prevention programs.

A lot of data preparation had to be done. For example, only older adults, aged between 65 and 85 years old, participate in the programs. In an interview with Mr. Hendriks, it was confirmed that there are no adults with the age of 85 or higher participating in the programs (Hendriks, interview, 2019). Therefore, the adults aged above 85 are excluded from the dataset.

Another example is that multiple datasets needed to be created, because multiple DOTs can be created by a physician as a result of a single fall incident. All the DOTs need to be included in the dataset to analyze the effect of the programs on the hospital costs while only the most severe DOT per fall incident needs to be included in the dataset to assess the number of fall incidents. In Appendix B, more details can be found on several other data preparation activities. The complete python code is presented in Appendix G.

5.3.2 Type, severity and costs of injuries associated with falls

As mentioned in section 5.1, the diagnoses related to fall incidents were selected and classified in accordance with Emergency Physician Annemarie van der Velden (Van der Velden, interview 1, 2019; Van der Velden, interview 2, 2019). The relevant diagnoses-treatment combinations were divided into six categories. A diagnoses-treatment combination with classification 1 indicates that the severity of the fall was relatively low (see patient two in table 1) and a fall with classification (or severity) 6 is a fall with major consequences (see patient one in table 1). It should be noted that fall incidents of all severity levels resulted in a visit to the ED of a hospital, and are already quite severe as most fall incidents do not require medical attention. Details about the different severity levels of the relevant diagnoses can be found in Appendix F.

In the following figure, the frequency, type, severity, and costs of the selected diagnoses related to fall incidents for community-dwelling elderly are shown. The column 'Number of DOTs' indicate the total number of a specific type of injury in one year (September 2017 until September 2018). The elderly population aged above 65 in both the intervention- and the control group are included in this analysis.

Table 2: Frequency, type, severity and costs of injuries caused by falls

Diagnoses	Number of DOTs	Severity	Average cost of single DOT
Head injury	250	2	€526
Femur, proximal (+collum)	184	6	€6080
Contusion	176	2	€644
Commotio / contusio cerebri	132	2	€584
Wrist	87	4	€1190
Humerus proximal and shaft	67	5	€2266
Multiple contusions	52	2	€548
Pelvis or sacrum	43	5	€1867
Shoulder (humerus)	36	4	€1259
Ankle	32	5	€2830
Vertebral column	26	5	€857
Clavicle	24	4	€1577
Phalanges of the hand	19	4	€498
Femur other	17	6	€6260
Other diagnoses (17)	140	4 & 5 & 6	€1643
Total	1,285		

As can be concluded from table 2, falls can cause many types of fractures and the differences between average DOT-costs are substantial: the average costs per DOT increases dramatically with a higher severity, especially between severity 5 and 6. Most of the DOTs, however, are in the second severity category.

5.3.3 The average yearly hospital expenditures per elderly per age group

To get a more thorough understanding of the treatment costs of injurious falls, the yearly hospital expenditures per age group of the areas Dordrecht-East, Dordrecht-West, Sliedrecht, and Zwijndrecht are depicted in figure 12.

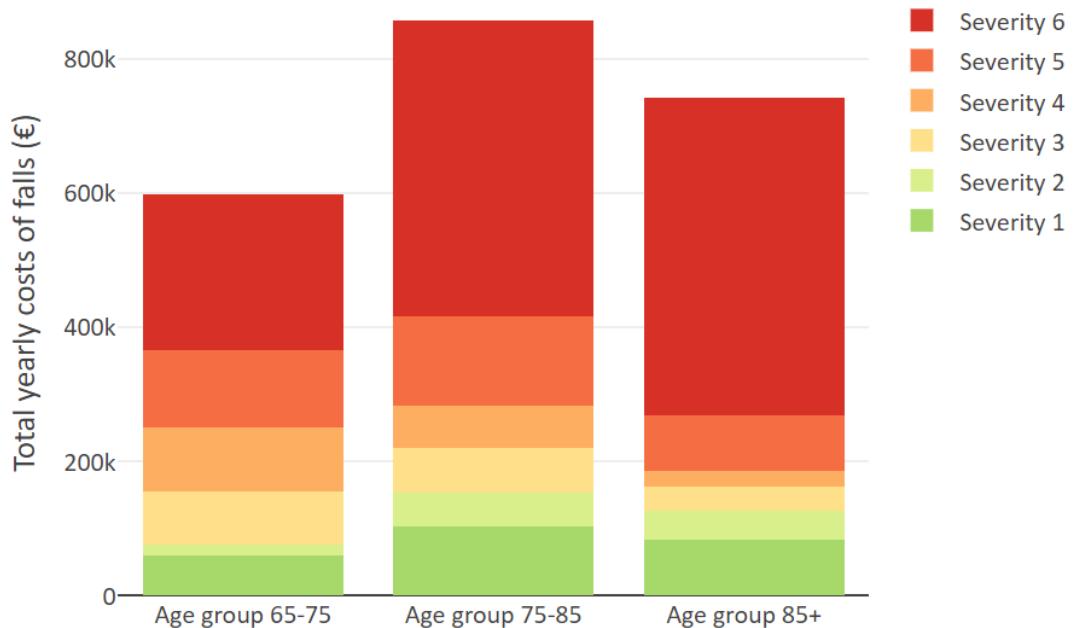


Figure 12: Total yearly costs of falls per age group

The total yearly hospital expenditures of falls of the community-dwelling elderly population living in the intervention- and control group are €2.196.177. The total population of older adults in the age-group 65-75 in these areas is 17.977 (58% of the total elderly population). The total fall-related hospital costs are €598.460, which is only 27% of the total costs. The older adults aged 75-85 account for 39% of the total costs (€856.465) while only 31% of the population is aged between 75 and 85 (total population is 9.834). There are 3.354 elderly aged above 85 (11% of the total population) living in the targeted areas (Appendix C). Together they account for a staggering 34% of the total yearly hospital expenditures (€741.251).

These numbers emphasize the fact that fall-risk increases as the age of older adults increases. Moreover, figure 12 illustrates that the share of severity six injuries also increases by age. It should be noted that elderly above 85 are not fit to participate in the fall prevention programs, and therefore will be excluded from the dataset (Hendriks, interview, 2019).

5.3.4 Total estimated healthcare costs of fall incidents

The frequency and severity of injurious fall incidents directly influence the hospital expenses made through the ZVW. After an injurious fall incident, several other forms of (long term) care are often required for an elderly to recover from a fall. As described in 3.4.1, these costs are covered through the WLZ and WMO, but no data is available about these expenses for the population living in the control- and intervention group.

However, the Dutch Consumer Safety Institute (VeiligheidNL) has estimated the average total healthcare costs of a fall incident per age group in the ZVW, WLZ, and WMO with data from their Injury

Surveillance System (LIS). The results of their analysis, in combination with the results from the DID method (effect on the number of fall incidents), will be used to determine the effect of the programs on the total healthcare costs. The estimated integral healthcare costs per age group are shown in the table below (VeiligheidNL, 2017, p.34):

Table 3: Estimated total healthcare costs per injurious fall per age group (VeiligheidNL, 2017, p.34)

Age group	Estimated total healthcare cost per fall
65-75	€3.600
75-85	€9.800
85+	€11.300

5.4 Sample of data used to perform the DID analysis

To get a better understanding of the data which will be used in the DID analysis to determine the effect of fall prevention programs, a sample of this data is shown in the table below. It contains the demographic data, number of falls, and total hospital expenditures per neighbourhood in year 2016-2017.

Table 4: Sample of data: demographic data, falls, costs DOTs per neighborhood in year 16-17

Year	Zip code	Neighborhood	Group	Age group 65-75			Age group 75-85		
				Population	# injurious falls	Total costs DOTs	Population	# injurious falls	Total costs DOTs
2016-2017	3311	City centre	Control	1869	37	€41,290	743	32	€85,045
2016-2017	3312	Indisch Buurt	Control	895	17	€31,245	350	13	€29,040
2016-2017	3314	Krispijn	Control	1340	25	€23,435	604	18	€27,400
2016-2017	3315	Stadspolder	Intervention	1409	29	€53,170	724	29	€66,635
2016-2017	3317	Crabbehof	Intervention	1389	43	€73,030	930	47	€91,610
2016-2017	3318	Sterrenburg	Intervention	835	28	€55,280	618	22	€38,780
2016-2017	3319	Dubbeldam	Intervention	1295	30	€45,560	944	55	€140,430
2016-2017	3328	Sterrenburg	Intervention	2081	47	€118,250	896	58	€102,550
2016-2017	3331	Zwijndrecht	Control	1078	20	€24,910	609	27	€49,510
2016-2017	3332	Zwijndrecht	Control	1503	35	€47,580	1179	48	€91,645
2016-2017	3333	Zwijndrecht	Control	638	10	€10,780	360	19	€40,725
2016-2017	3334	Zwijndrecht	Control	939	25	€21,000	451	17	€40,395
2016-2017	3335	Zwijndrecht	Control	613	12	€16,125	197	12	€33,910
2016-2017	3361	Sliedrecht	Control	628	14	€19,170	316	15	€23,635
2016-2017	3362	Sliedrecht	Control	1112	18	€33,230	815	36	€70,050

The DID analysis will be done on a neighborhood level or, more specifically, on a zip code (4 digit) level. As can be seen in the table above, there are 15 observations per year as there are 15 zip codes (4 digits) in the control- and intervention group areas. As there are four analysis years, there are in total 60 observations to determine the effect of the fall prevention programs. With the data from table 4, it is possible to calculate the number of fall incidents per 100 elderly and the total average hospital costs per elderly. These numbers are shown in table 5. As described in chapter 4, the effect of the fall prevention programs is assessed on these two dependent variables using the DID method.

Table 5: Number of falls per 100 elderly and hospital expenditures per group per year

Variable	2014-2015		2015-2016		2016-2017		2017-2018	
	Intervention group	Control group						
Number of falls per 100 elderly	3.94	3.32	3.94	3.18	3.49	2.77	3.02	2.81
Average hospital expenditures per elderly	€ 63.43	€ 63.33	€ 70.80	€ 58.18	€ 70.61	€ 46.80	€ 52.34	€ 52.28

5.5 Reproducibility and replication of the research

In the python model, which is created to assess the effect of the fall prevention programs, all the data preparation- and processing steps are clearly explained. Together with the excel file ‘Selection relevant diagnoses and classification’, containing information of the DOTs relevant for the analysis of fall incidents, the research is easily reproducible by anyone with a basic understanding of data analysis.

In this python model, the raw hospital datasets out of the HiX-system, and other raw datasets, as explained in section 5.3, are processed within a few minutes using mainly the library ‘Pandas’ within package ‘NumPy’. The latter is a fundamental package for scientific computing with Python. It provides space-efficient multidimensional arrays (close to hardware) and has sophisticated other functions (Bressert, 2012). The library ‘Pandas’ is built on top of NumPy and provides high-level data structures and manipulation tools for data analysis such as arithmetic operations and reductions, labeled axes, flexible handling of missing data and time series (Downey, 2012). The visualizations of the various figures have been done using the package ‘Plotly’. These interactive visualizations can be easily shared via the online Plotly-platform. The package ‘Statmodels’ has provided tools to do all the statistical analysis and tests.

6

Results of the case study

In section 6.1, the effect of the fall prevention programs on the number of fall incidents is assessed using the DID method. The same method is used to determine the effect of the programs on hospital expenditures in section 6.2. A possible reduction in falls does not only result in lower hospital costs but reduces costs across the entire healthcare sector. The total reduction in healthcare costs is estimated using the results of section 6.1 in combination with results of research done by The Dutch Consumer Safety Institute in section 6.3.

6.1 The effect of the programs on the number of fall incidents

6.1.1 Examining the pre-intervention trend of the control- and intervention group

The common trend assumption (CTA) is a critical assumption to ensure the internal validity of the DID model. If in the absence of the treatment, the average outcomes for treated and control groups have followed parallel trends over time, one can measure the average treatment effect for the treated subpopulation. Pre-treatment data is used to determine whether the CTA assumption holds (Wing et al., 2018).

To check the common trend assumption, the trend of the number of falls per 100 elderly per year of both the control- and intervention group will be compared. If the trend of the control group in the pre-treatment period is the same as the trend of the intervention group, the common trend assumption holds and the DID method model can be used to estimate the effect of the programs (Abadie, 2005). In figure 13, the fall incidents per 100 elderly of both groups are shown over time.

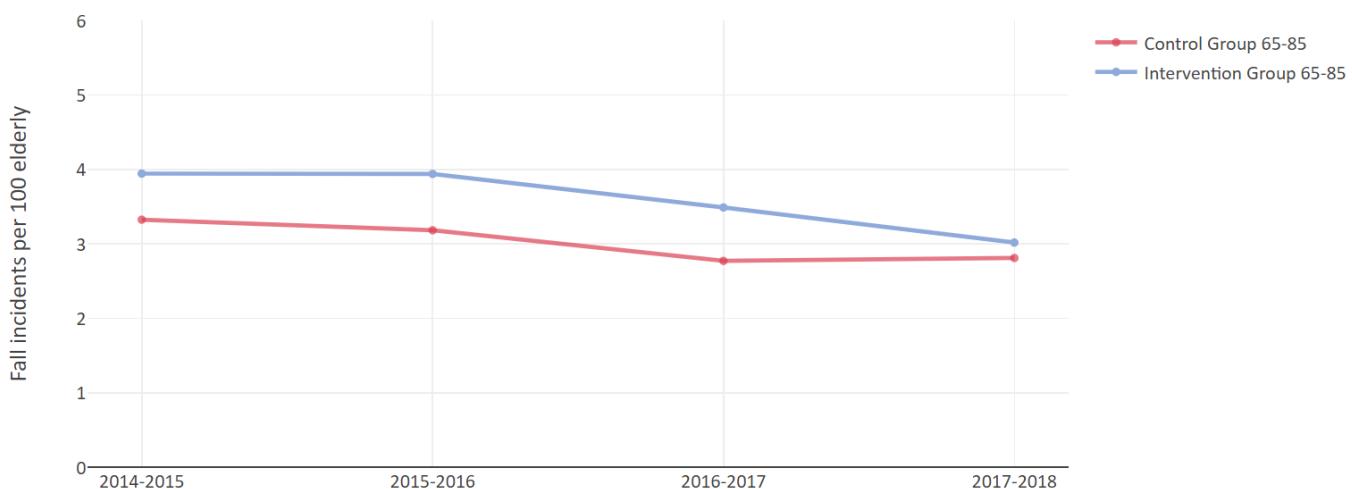


Figure 13: Pre-intervention trend in number of fall incidents per 100 elderly of both groups

Figure 13 shows that the control group has a slight increase in injurious fall incidents per 100 elderly between period 2016-2017 and 2017-2018, while the falls in the intervention group decrease in the same period. This suggests that fall prevention programs decrease the number of injurious fall incidents. In the figure below, the years 2016-2017 and 2017-2018 are depicted to show the increase- and decrease in the number of falls per 100 elderly per severity in the control- and intervention group.

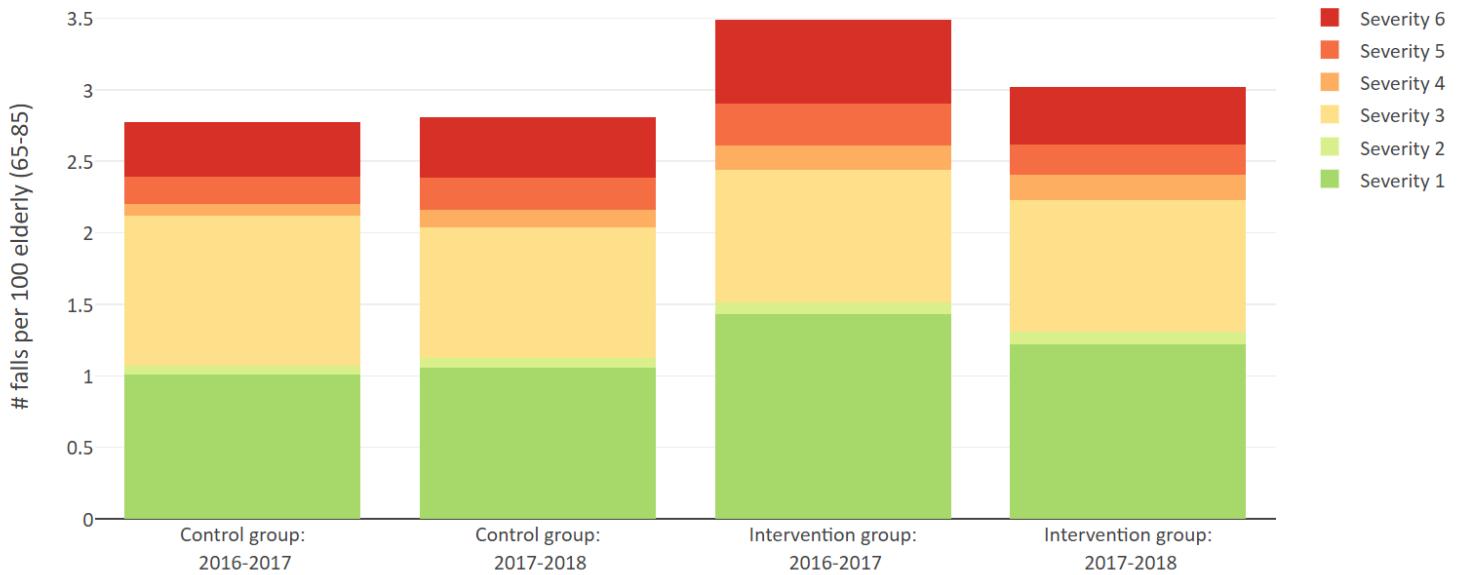


Figure 14: The number of falls per 100 elderly per severity in years 2016-2017 and 2017-2018

The chart also suggests that the share of falls with severity 6 has reduced in the intervention group in 2017-2018 in comparison with the year 2016-2017, while the share of falls with severity six increases between the two years of the control group.

When reviewing figure 13, it seems that the control group has a similar trend as the intervention group in the pre-treatment period (2014-2015, 2015-2016, and 2016-2017). By using the DID method, described in chapter 4.2.3, one can determine whether the CTA holds. In this analysis, the DID method is used to determine whether there is a difference in the trends between the groups in the pre-intervention years. Two analyses will be done to determine whether the CTA holds: checking the trend between year 2014-2015 and year 2015-2016, and year 2015-2016 and 2016-2017. The CTA holds when the coefficient of the DID estimate is close to 0 and the p-value is high.

6.1.1.1 Testing the CTA in pre-intervention year 2014-2015 and 2015-2016

The results of the WLS-regression, to examine whether the CTA holds between year 2014-2015 and 2015-2016, are shown in table 6. The table containing the data used to conduct this analysis can be found in Appendix E1.

=====						
Dep. Variable:	CTA_Test_1415_1516_Falls_per_100_Elderly		R-squared:		0.198	
Model:		WLS	Adj. R-squared:		0.105	
Method:		Least Squares	F-statistic:		2.136	
Date:		Sun, 30 Jun 2019	Prob (F-statistic):		0.120	
Time:		11:57:21	Log-Likelihood:		-32.595	
No. Observations:		30	AIC:		73.19	
Df Residuals:		26	BIC:		78.79	
Df Model:		3				
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.05	0.95]
const	3.3247	0.250	13.275	0.000	2.897	3.752
Ig	0.6191	0.392	1.578	0.127	-0.050	1.288
P1t	-0.1425	0.352	-0.405	0.689	-0.742	0.457
Ig * P1t	0.1380	0.552	0.250	0.804	-0.803	1.079

Table 6: CTA test results - year 14-15 and 15-16 (#falls per 100 elderly)

The coefficient of Ig * P1t is close to zero and has a high p-value (0.80). This indicates that there is a similar trend between the control- and intervention group in this pre-intervention period. Therefore, the CTA holds. However, it is necessary to check whether the CTA holds for year 2015-2016 and 2016-2017. This will be done in the next section.

6.1.1.2 Testing the CTA in pre-intervention year 2015-2016 and 2016-2017

In table 7, the WLS-regression results are presented to investigate whether the CTA holds between year 2015-2016 and 2016-2017. The table containing the data used to conduct this analysis can be found in Appendix E2.

Table 7: CTA test results - year 15-16 and 16-17 (#falls per 100 elderly)

=====						
Dep. Variable:	CTA_Test_1516_1617_Falls_per_100_Elderly		R-squared:		0.323	
Model:		WLS	Adj. R-squared:		0.255	
Method:		Least Squares	F-statistic:		4.767	
Date:		Sun, 30 Jun 2019	Prob (F-statistic):		0.00307	
Time:		11:58:54	Log-Likelihood:		-42.167	
No. Observations:		45	AIC:		94.33	
Df Residuals:		40	BIC:		103.4	
Df Model:		4				
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.05	0.95]
const	3.2962	0.191	17.250	0.000	2.974	3.618
Ig	0.6889	0.236	2.918	0.006	0.291	1.087
P1t	-0.0863	0.232	-0.372	0.712	-0.477	0.304
P2t	-0.5251	0.283	-1.855	0.071	-1.002	-0.048
Ig * P2t	0.0289	0.404	0.072	0.943	-0.651	0.709

The coefficient of Ig * P2t is close to zero and has a high p-value (0.94). This indicates that there is a similar trend between the control- and intervention group in this pre-intervention period. As the CTA holds in all the available pre-intervention years, the DID method can be used to assess the effect of fall prevention programs on the number of injurious fall incidents. The effect will be determined in the next section.

6.1.2 The estimated effect of the programs on the number of injurious fall incidents

The results of the WLS-regression, to examine the effect of the programs on the number of injurious fall incidents, are shown in table 8. The table containing the data used to conduct this analysis can be found in Appendix E3.

Table 8: WLS-regression results to examine the effect of the programs on the number of falls

Dep. Variable:	Falls_per_100_Elderly_65_85	R-squared:	0.355			
Model:	WLS	Adj. R-squared:	0.295			
Method:	Least Squares	F-statistic:	5.947			
Date:	Sun, 30 Jun 2019	Prob (F-statistic):	0.000189			
Time:	12:00:55	Log-Likelihood:	-52.360			
No. Observations:	60	AIC:	116.7			
Df Residuals:	54	BIC:	129.3			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.05	0.95]
const	3.2922	0.171	19.240	0.000	3.006	3.579
Ig	0.6988	0.180	3.893	0.000	0.398	0.999
P1t	-0.0863	0.217	-0.397	0.693	-0.450	0.278
P2t	-0.5134	0.216	-2.377	0.021	-0.875	-0.152
P3t	-0.4818	0.259	-1.862	0.068	-0.915	-0.049
Ig * P3t	-0.4918	0.353	-1.391	0.170	-1.083	0.100

As expected, the variable I_g , indicating whether the observation is in the control- intervention group (regardless of the analysis year), has a positive coefficient. In figure 13, this is also visible: there is a gap between the intervention- and control group in the number of fall incidents per 100 elderly in all years under study. However, the trend is the same pre-intervention, and therefore, the common trend assumption holds. Variables $P1_t$, $P2_t$, and $P3_t$ have a negative coefficient, meaning that the number of fall incidents per 100 elderly was slightly trending down over time.

The coefficient of the variable $I_g * P3_t$ provides the Difference-in-Differences estimator, which is the average estimated effect of the fall prevention program. The negative coefficient suggests that the average weighted effect of the fall prevention programs on the number of injurious falls per 100 elderly is -0.49. In 2017, the population in Dordrecht-East (the intervention area) of community-dwelling elderly aged between 65 and 75 was 7.123, and the population aged between 75 and 85 was 4.178 (Appendix C). Therefore, it is estimated that in total 55 injurious falls have been prevented in the year 2017-2018 because of the fall prevention programs of which 35 falls in the age group 65-75, and 20 falls in the age group 75-85.

The significance level of the DID-estimator ($I_g * P3_t$) is 0.17. Within the 95%-confidence interval, the effect on the number of injurious fall incidents per 100 elderly is between minus 1.083 and plus 0.100. This means that the effect of the fall prevention programs varies between 122 (prevented) falls and -11 (prevented) falls. With the current p-value, the null hypothesis, stating that the fall prevention programs do not have any effect on the number of injurious fall incidents, cannot be rejected. The reason that the estimator is not significant is partly due to the fact that the number of observations is low ($N=60$). Furthermore, the F statistic is under 10, indicating that there is a weak instrument problem, and the R-squared value (0.355) suggest a low effect size (Moore, Notz & Fligner, 2013).

As the treatment group has only been exposed to the treatment for one year, there is insufficient data to find a significant effect below the 0.05 threshold. However, as the p-value is 0.17, a large part within the confidence interval range indicates that the fall prevention programs do have a negative effect on the number of falls (on average 55 prevented injurious falls).

6.2 The effect of the programs on the hospital expenditures

6.2.1 Examining the pre-intervention trend of the costs of both group groups

As the data suggests that the fall prevention programs do affect the number of injurious falls, the programs might affect the hospital expenditures as well. To check whether the DID method can be used, the trend of the average hospital expenditures per elderly of both the control- and intervention group in the pre-intervention period will be assessed. If the trend in the pre-treatment period is the same as the trend of the intervention group, the common trend assumption holds, and the DID method can be used. In figure 15, the average hospital expenditures per elderly are shown over the last four years.

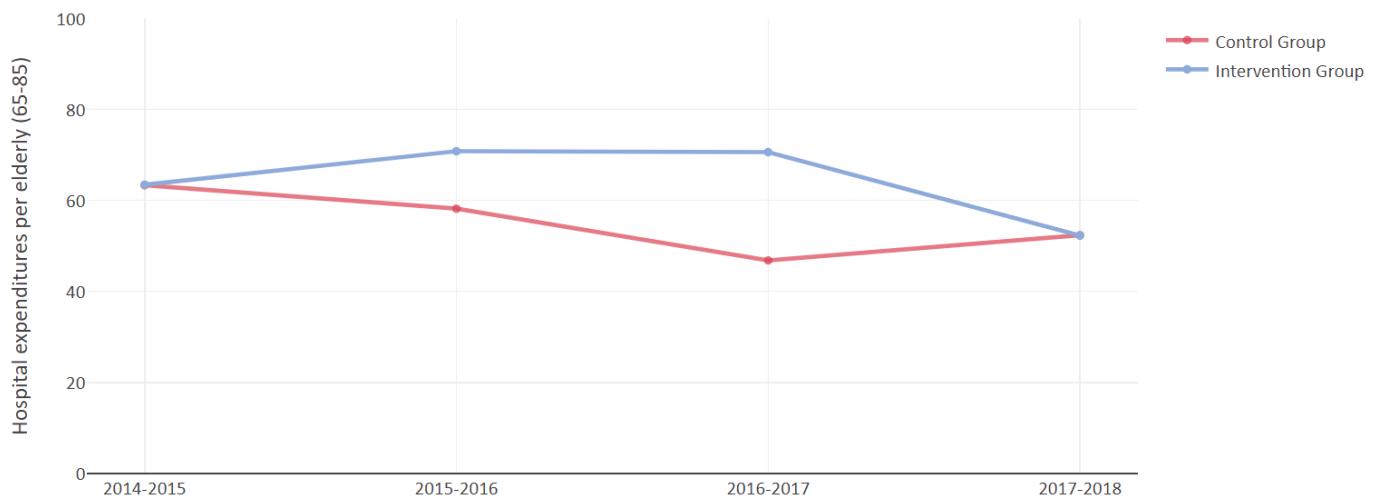


Figure 15: Pre-intervention trend in hospital costs of both groups

In the pre-treatment period (2014-2015, 2015-2016, and 2016-2017), the control group does not show a similar trend as the intervention group. Just by visual inspection, the conclusion can be drawn that the DID method cannot be used to determine the effect of the fall prevention programs on hospital expenditures. In appendix D, the results of the test, using the DID method to determine whether the CTA holds in the pre-intervention period, are shown. As expected from reviewing figure 15, these results indicate that there is a difference in the trend between the control- and intervention group in the pre-intervention period. Therefore, the CTA does not hold and the DID method cannot be used to assess the effect of fall prevention programs on the hospital expenditures.

In the next paragraphs, the explanation for these diverging trends in years 2014-2017, and the converging trend between years 2016-2017 and 2017-2018, will be given.

6.2.2 Explanation of the diverging- and converging trends

The diverging- and converging trends occur because of the enormous differences in DOT-prices between the injuries caused by fall incidents. The DOT-prices can be reviewed in table 2 in section 5.3.2. Especially the fractures in severity level 6 (mainly hip fractures) are expensive and, therefore, slight deviations in the number of fall incidents resulting in a hip fracture can have a major impact on the average hospital expenditures per elderly. The sample size in both the control- and intervention group is not large enough to remove this disruptive effect.

The diverging- and converging trends are best explained by the data presented in table 9. Only the elderly population aged between 65 and 85 in both the intervention- and the control group are included in this analysis.

Table 9: Frequency and costs of injuries in order to examine trends

	2015-2016 # DOTs	€	2016-2017 # DOTs	€	2017-2018 # DOTs	€	Grand Total (# DOTs)	% of total # DOTs (5575)	Total costs 2014-2018	% of total costs (€6.335k)
Contusion	147	€ 89k	131	€ 61k	118	€ 71k	545	14.3%	€ 273k	4.3%
Control group	62	€ 29k	59	€ 35k	63	€ 38k	254	6.7%	€ 126k	2.0%
Intervention group	85	€ 60k	72	€ 26k	55	€ 34k	291	7.6%	€ 147k	2.3%
Wrist fracture	83	€ 90k	89	€ 127k	69	€ 78k	326	8.5%	€ 382k	6.0%
Control group	49	€ 56k	59	€ 74k	40	€ 48k	190	5.0%	€ 229k	3.6%
Intervention group	34	€ 34k	30	€ 52k	29	€ 30k	136	3.6%	€ 152k	2.4%
Femoral fracture	122	€ 768k	122	€ 741k	118	€ 635k	477	12.2%	€ 2.848k	44.9%
Control group	73	€ 446k	60	€ 338k	72	€ 385k	263	6.7%	€ 1.559k	24.6%
Intervention group	49	€ 322k	62	€ 403k	46	€ 250k	214	5.5%	€ 1.289k	20.3%

The DOT-price of a single hip (femoral) fracture is above 6.000 euros per DOT. The total hospital expenditures of these 477 DOTs were around 2.80 million euros in the last four years. This means that 12.2% of the injurious falls of elderly in age group 65-85 is a femoral fracture and that these fractures account for 49.9% of the total costs. Therefore, a decrease of only 16 femoral fractures in the intervention group in 2017-2018 (compared to 2016-2017) account for a large part of the decrease in average yearly hospital expenditures per elderly as can be seen in figure 15. An increase of 12 Femur-DOTs in the control group in the same period led to a significant increase in hospital costs per older adult. This explains the converging trend between 2016-2017 and 2017-2018. The diverging trend between 2015-2016 and 2016-2017 is also caused by a slight decrease- or increase of femoral fractures between the control- and intervention group.

Table 9 also shows the costs and frequency of a minor injury (a contusion) and a moderate injury (a wrist fracture). The impact of these two injuries on the hospital expenditures will be compared to the impact of femoral factors to support the point made in the previous paragraph.

The average cost of a wrist fracture DOT is € 1,190, and the costs of a single contusion-DOT is € 644. Approximately 9% (326 DOTs) of the elderly who ended up in the emergency department after a fall came in with a wrist fracture and the combined costs of these DOTs (€ 381,655) is 6% of the total hospital costs (due to fall incidents). Also, the costs of 545 contusions are only 4.3% of the total costs. These numbers illustrate that the impact of these injuries is significantly less than femoral fractures.

Because of these diverging- and converging trends, the common trend assumption does not hold, and the DID method cannot be used to determine the effect of the fall prevention programs on the hospital expenditures. However, as the fall prevention programs have shown to decrease the number of injurious falls in section 6.1, a cost reduction is expected across the entire healthcare sector. In the next paragraph, the healthcare cost reduction is estimated by combining the results of research done by the Dutch Consumer Safety Institute and the results of this thesis presented in section 6.1.

6.3 The effect of the programs on the total healthcare expenditures

The Dutch Consumer Safety Institute has estimated the average total healthcare costs of a fall incident per age group in the ZVV, WLZ, and WMO with data from their Injury Surveillance System (VeiligheidNL, 2017). The results of their analysis (presented in table 3) in combination with the results from the DID method (effect on the number of fall incidents) are used to determine the effect of the programs on the total healthcare costs. The estimated effect of the fall prevention programs on the total yearly healthcare costs are shown in figure 16.

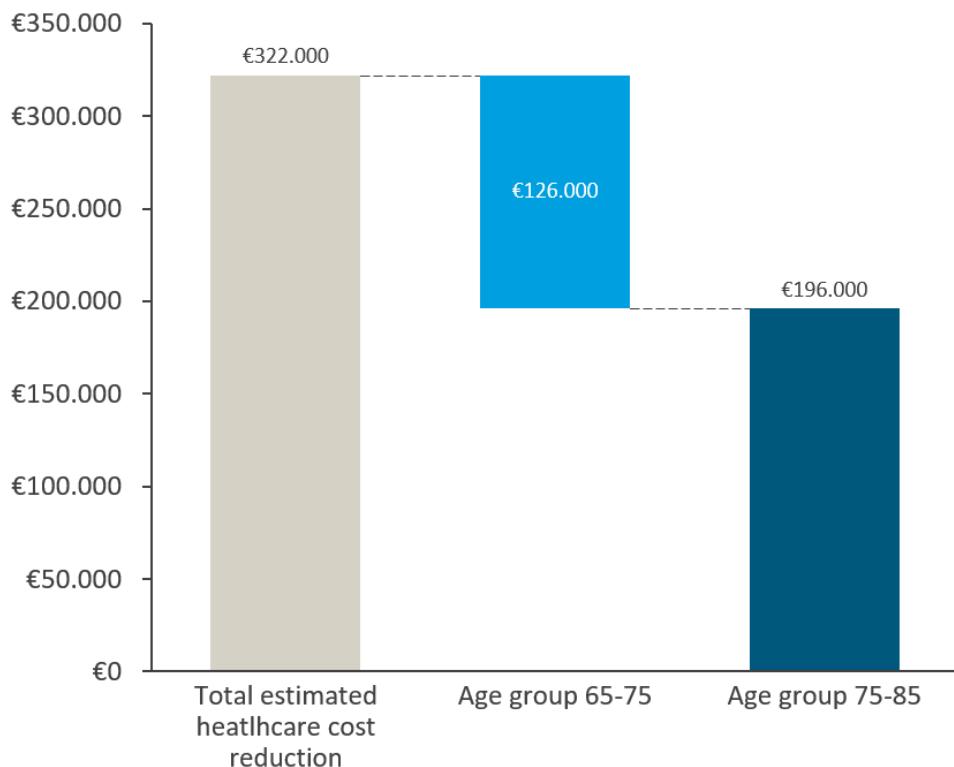


Figure 16: Yearly estimated costs reduction because of fall prevention programs

To validate these results, an expert in the field of fall prevention programs and HIB from the Dutch Consumer Safety Institute, has checked these results and confirmed that a yearly healthcare cost reduction of €322,000 would indeed be realistic given the number of participants (Kloet, interview, 2019). These results will also be used in the next chapter to assess whether the reduction in healthcare costs outweighs the costs to implement and run the fall prevention programs.

7

The applicability of a HIB

At this point, the case study in Dordrecht is finished. The results of this case study indicate that fall prevention programs are effectively reducing the risk of falling among the elderly population (assuming that the average estimated effect of the fall prevention programs is correct). Therefore, it is useful to explore the possibilities to encourage local entrepreneurs to implement fall prevention programs. There is a substantial financial barrier for local implementers to set up the programs, and a HIB holds great promise to be an applicable instrument to provide local implementers with the funding needed to set up the programs. The success factors and barriers of this innovative financing instrument will be reviewed in this chapter.

First, the economic feasibility of a HIB will be assessed by comparing the benefits of the fall prevention programs to the implementation- and operational costs (section 7.1). Furthermore, a possible concept of a HIB will be described in section 7.2. In section 7.3, the governance- and legal barriers to set up a HIB are described. Finally, the success factors of a HIB are listed in section 7.4.

7.1 The costs and benefits of fall prevention programs

A precondition for a HIB is that the expected benefits of the implemented program outweigh the operational- and implementation costs. VeiligheidNL (2017) estimated that the total healthcare costs of a single injurious fall for an adult aged between 65-75 are around 3.600 euro, and for an adult aged between 75-85, the costs per fall have predicted to be 9.800 euro. On average about 55% of the required care after a fall is provided through the ZVW, 38% through the WLZ, and 7% through the WMO. The results of the case study indicated that 55 injurious falls were prevented in the year 2017-2018 as a result of the fall prevention programs of which 35 falls in the age group 65-75, and 20 falls in the age group 75-85. This means that the yearly total cost reduction is estimated to be 322.000 euro due to the implementation of the programs in Dordrecht-East.

As described in section 3.5.1, the yearly operational costs of the fall prevention programs are around 99.717 euro, and 42.865 euro was spent in the years before implementation to screen elderly and to develop the programs. The costs and benefits are compared in the figure below.

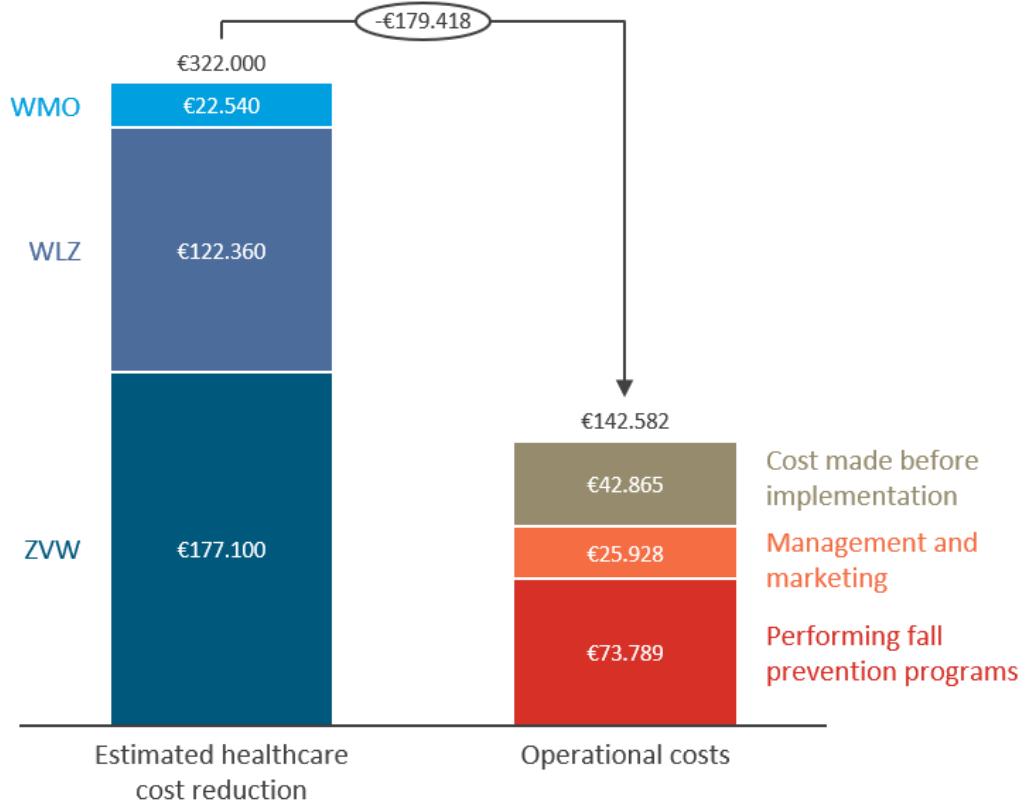


Figure 17: Economic feasibility of fall prevention programs

Figure 17 clearly shows that the yearly benefits of the fall prevention programs outweigh the costs by 179.418 euros. However, when implementing programs using a HIB, extra costs will be made to pay the independent assessor, for financial- and legal services or advice, and to pay the local implementer or intermediary (Kloet, interview, 2019). In the current situation, the health insurer partly reimburses older adults for participating in fall prevention programs; these reimbursements are not included in this analysis.

On the other hand, additional benefits of fall prevention might occur such as less informal care, improvement of the quality of life, and greater social participation. These benefits are currently challenging to monetize and further research is required to make a reasonable estimation of these benefits.

7.2 A possible concept of a HIB to set up fall prevention programs

The concept of a HIB was briefly described in section 2.2.2. The next paragraphs and the figure below explain a more complicated concept of a HIB to set up fall prevention programs.

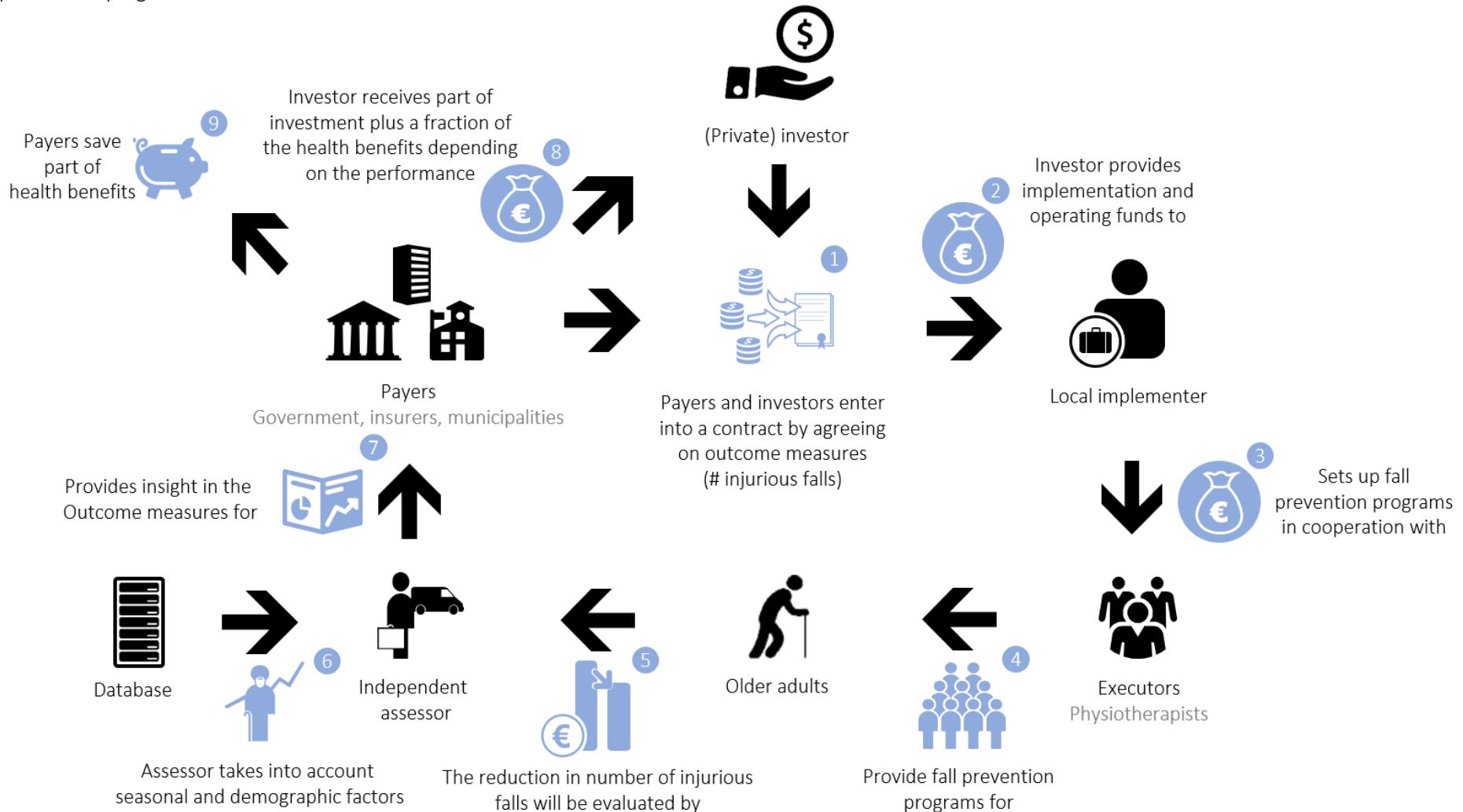


Figure 18: The concept of a HIB

This concept does not take governance- or legal barriers into account. These barriers are discussed in section 7.3. Under this assumption, the following stepwise approach describes the concept of a HIB and the elements needed in order to make the HIB a success (Kloet, interview, 2019):

1. The municipality sees an opportunity to reduce the number of falls by encouraging local entrepreneurs to implement fall prevention programs using a HIB and attracts an investor. As the government, insurers, and municipalities will benefit from the fall prevention programs through a reduction in fall-related healthcare costs, they enter into a contract by agreeing on outcome measures such as the number of injurious falls. Also, an independent assessor should be appointed, the evaluation method needs to be determined, and a reasonable time horizon should be made.
2. The investor provides operating funds to a local implementor (or contractor). In this step, the investors can enter into a pay-for-performance contract with the local implementers and the executors. These parties, responsible for developing, implementing, and performing the fall prevention programs, will be paid based on the number of participants. This will create an extra incentive to attract as many participants as possible.
3. The fall prevention programs will be implemented by the executors (physiotherapists) coordinated by the local implementer. They collaborate with other stakeholders such as (emergency) physicians, general practitioners, district nurses, geriatricians, senior advisors, and occupational therapists to promote fall prevention programs. The municipality can help to connect these various stakeholders.
4. The executors provide fall prevention programs for older adults free of charge.
5. An assessor will evaluate the reduction in the number of injurious falls every year. This evaluator should be independent and should gain no benefits from all possible outcomes that the evaluation may deliver. Moreover, the evaluation should be publicly available in order to be as transparent as possible. The evaluator could be a trusted party such as VeiligheidNL.
6. The independent assessor checks the behavior of the performance indicators taking into account seasonal and demographic factors. The evaluator should have access to all the data required, and the stakeholders involved should provide missing data without delay.
7. The controller provides insight into the performance of the fall prevention programs for the payers based on pre- and post-intervention data.
8. Assuming that the programs have a measurable reducing impact on the number of injurious falls, the payers refund (part of the) investment done by the investor plus a return. This is done based on the predetermined outcome measures.
9. The payers save a part of the health benefits to maintain the fall prevention programs when the contract ends.

7.3 Barriers to create a HIB regarding governance or law

The concept of a HIB as depicted in figure 18, might be hard to implement due to governance- and legal barriers. As this chapter only explores the possibility of a HIB, only the most important barriers are described.

7.3.1 Legal barriers

In the current Dutch healthcare system, there is a legal barrier for health insurers to pay out profits to private parties. Also, care offices cannot use the funds of the WLZ to repay investors after health benefits have been achieved due to the implementation of fall prevention programs. As can be seen in figure 17, funds from the municipality through the WMO are not sufficient to cover the operational- and implementation costs of fall prevention programs. The ministry of VWS should be flexible in making exceptions to set up a HIB regarding this topic. The ministry has done that for the SIB ‘social Hospital’ (described in section 2.2.2.1). According to Saskia Kloet (Kloet, interview, 2019), the ministry has recently made an exception to set up the first HIB in the south of the Netherlands.

7.3.2 Governance barriers

In an interview with Saskia Kloet (Kloet, interview, 2019), it came to light that payers find it hard to believe that a valid evaluation method can be created to assess the impact. This thesis has developed a method to assess the impact of fall prevention programs on the number of injurious fall incidents. However, the partners in a HIB need to agree on an entire monitoring plan in which it is clear what is being measured, how this is done, for how long this will be done and by whom the performance will be evaluated. It will be hard to create a monitoring plan that both the payers and investors will agree on. Moreover, elderly in a municipality are insured by several different health insurers making it even harder to reach consensus as multiple health insurers might participate in these negotiations (Kloet, interview, 2019).

The payments of reductions in healthcare costs to private investors are still unexplored territory. Health insurers are, therefore, cautious about their possible role in a HIB. Health insurers do not expect savings in the (medium) long term due to fall prevention programs. They assume that any savings in the short term will be nullified by higher costs of care in the last year of the life of an elderly (Kloet, interview, 2019).

Health insurers also point out that it is highly complex to determine the actual hospital production. A negotiation-game of several years is often needed to reach consensus about this topic. Therefore, health insurers are sceptical about the possibility to quickly and clearly determine the actual cost reduction in hospital expenditures (Kloet, interview, 2019).

Another issue is that health insurers are not convinced that prevention results in savings in the short term. The current Dutch healthcare system is based on payment per medical procedure, which results in a strong production incentive. This does not encourage prevention: a reduction in fall incidents will decrease the revenue of a hospital. In practice, a hospital will make an effort to maintain its revenue. When fall prevention programs result in fewer hospital admissions, a hospital will compensate for this turnover loss by providing extra care in other departments of the hospital (Kloet, interview, 2019). However, some care providers, such as the ASZ, have made lump sum agreements with insurers. At these hospitals, the reduction of the number of admissions does not decrease the revenue, and the hospital personnel has an incentive to increase the number of participants to relieve the pressure on the emergency department. However, most of the hospitals in the Netherlands have not made lump sum agreements (Kloet, interview, 2019).

Another issue regarding governance is that there are incentives for several parties to influence the evaluation process as they benefit from successful outcomes such as the local implementer and the investors. This creates an incentive for these stakeholders to influence the outcomes positively. These incentives are inherently included in a HIB with payments based on outcomes and might influence the effectiveness of a HIB.

Stakeholders have different incentives in the concept illustrated in figure 18. Hence, the evaluation should be performed by an independent assessor. As this actor needs to be paid for its evaluation services, it can be argued that this actor will never be completely independent. Therefore, it will be important that the evaluator is paid by all the parties involved in the HIB, rather than by a single stakeholder.

Another concern is that the independent assessor will have to deal with confidentiality and privacy issues as the evaluator needs to have access to hospital data. These confidentiality and privacy issues must be sorted out before implementing fall prevention programs using a HIB (Kloet, interview, 2019).

A pilot project is needed in which fall prevention programs are implemented using a HIB to find out whether these barriers can be surmounted. Courage from investors, local entrepreneurs, and payers is needed to set up the first HIB (Kloet, interview, 2019). Moreover, systematic reporting of falls per neighborhood should be encouraged to make it easier to analyze the impact of fall prevention programs in several municipalities.

7.3.3 Unanswered legal- and governance related questions

As this study has only explored the possibilities of a HIB, no solution is given to overcome the barriers described in the sections above. This paragraph elucidates on the (governance) questions that remain unanswered:

1. How can the legal barrier for health insurers and care offices, to pay out profits to private parties, be surmounted?
2. How can a monitoring plan, and corresponding evaluation method, be created that will be accepted by both the payers and investors?
3. Which party is suitable to act as the independent assessor?
4. How can the actors deal with the confidentiality and privacy issues?
5. Which party is suitable to facilitate and guide the negotiations necessary to set up a HIB?
6. How can all the actors involved, including the various different health insurers, be brought together to agree on the several aspects of a HIB?
7. What are the (extra) organizational costs of a HIB?
8. How can the health insurers be convinced to partake in a HIB?
9. What policy can be implemented by the government to reduce the strong production incentive in hospitals?
10. What policy can be implemented by the government to create an (extra) incentive for health insurers to participate in a HIB?
11. Which (legal) elements should be included in a contract between investors and payers?
12. Which (legal) elements should be included in a contract between investors and local implementers or executors?
13. What other types of outcome measures, such as results of a questionnaire, can encourage payers and investors to partake in a HIB?

7.4 Success factors of a HIB to set up fall prevention programs

A HIB can provide many opportunities to facilitate the implementation of fall prevention programs in municipalities across the Netherlands. To emphasize the applicability of a HIB, the most essential success factors are listed below (Kloet, interview, 2019):

1. The reduction in healthcare costs (in ZVW, WLZ, WMO) outweighs the implementation- and operational costs of the fall prevention programs.
2. Investors reward implementers, not for their efforts, but based on their performance results.
3. The investor will carry the full financial risk. The local implementer, the executors (physiotherapists), and the caregiver will not have that risk. This stimulus can facilitate implementation in many regions across the Netherlands, resulting in a higher quality of life for older adults, and lower healthcare expenditures as elderly can live at home for a longer period of time longer. Also, current local implementers of fall prevention programs, such as Arno Hendriks, might have an opportunity to implement the programs on a larger scale.
4. The burden of proof is shifted from the implementor to the investors.
5. The HIB provides insight into the reduction in the number of injurious falls and healthcare cost that is directly related to the fall prevention programs, which makes the instrument sustainable and self-sufficient.
6. Investors are interested to invest in a cause that benefits society and can make a small profit.
7. Older adults are not required to pay for a fall prevention program and it is therefore more likely that they will participate.

8

Conclusion

Affordability of the Dutch healthcare sector is under enormous pressure due to an aging society. It is a challenge to maintain high-quality healthcare while at the same time controlling the rise of healthcare expenses. Fall prevention programs hold great promise to reduce healthcare expenditures by preventing falls among the community-dwelling elderly. In the current Dutch healthcare system, it is difficult for local entrepreneurs to get funding to develop and implement fall prevention programs as it is unclear what the real benefits are for the stakeholders where the potential savings end up. Therefore, an evaluation model is created to assess the effect of fall prevention programs on the number of injurious fall incidents and hospital expenditures of community-dwelling elderly. This evaluation model is used to assess the impact of fall prevention programs by conducting a case study. In addition, the possibilities to remove the financial barrier for local entrepreneurs to implement fall prevention programs, using the innovative financing instrument Health Impact Bond (HIB), were explored. The results of the case study have been used to assess the economic feasibility of a Health Impact Bond for fall prevention programs. Also, other governance- and legal barriers to implement fall prevention programs, using a HIB, were identified. Having analyzed and discussed the results, this research returns to the research question:

"How can the effect of fall prevention programs on the number of injurious fall incidents and healthcare costs of community-dwelling elderly be determined in order to explore the applicability of a Health Impact Bond?"

As it is unpractical and unethical to track the healthcare history of older adults who participated in the fall prevention programs, a method was developed to assess the effect of the fall prevention programs on the population of a region where the programs have been implemented using hospital data. The relationship between fall incidents and the implementation of fall prevention programs has been estimated by using a Difference-in-Differences design that nets out any time-invariant neighborhood characteristics and time-varying changes that affect the regions identically.

The elderly population, in a region where the programs are implemented and a region that is unaffected by this intervention, are compared. This method calculates the difference in outcomes between these two populations before the fall prevention programs were implemented and after the implementation. The difference between those two differences is the estimated effect of the intervention. Stakeholders can use this method and the python evaluation tool, developed during this study, to assess the effect of fall prevention implemented in other regions.

The results of the case study suggest that fall prevention programs are effectively reducing the risk of falling among the elderly population and will, therefore, reduce healthcare expenditures. However, the estimated effect of the programs on the risk of falling varies quite strongly. The same Difference-in-Differences design was unfit to assess the effect of fall prevention programs on the hospital expenditures due to enormous differences in costs between the injuries caused by falls. In order to assess the effect of fall prevention programs on the hospital expenditures, replication of this research is needed using a larger dataset, including a more extensive intervention- and control area. The research

is easily replicable as the python model can process other hospital datasets with only minor adaptations to the code.

However, it is challenging to collect the required hospital data due to privacy and confidentiality issues. Systematic reporting of the number of falls, the type of injuries, and the total healthcare costs of the injuries per region, should be encouraged. This way, the method and evaluation tool can be used to assess different types of fall prevention interventions and at the same time they can be improved.

Structural resources are needed to implement fall prevention programs for reaching and motivating the elderly, for the reimbursement of (extra) activities by parties and for financing the organizational costs to set up and manage the program. Currently, subsidies are occasionally provided by the municipality. However, these do not fully cover the development and implementation costs of the programs.

Assuming that the average estimated effect of the fall prevention programs is correct, fall prevention programs have proven to be an effective intervention. The intervention results in a reduction of healthcare costs that far outweigh the implementation- and operational costs of these programs. The reductions in healthcare expenditures are sufficient, not only to cover the required organizational costs and to be able to repay the investor, but also to finance an investment when funding has ended. With enough health benefits saved, the programs can continue to run this way, without the need for private investors.

Courage from investors, local entrepreneurs, and payers is needed to set up the first HIB. This cooperation is desperately needed, because making performance visible in healthcare is difficult, paying out the savings achieved to investors is still unexplored territory, and stakeholders need to agree on a method to evaluate the effect of the programs. The evaluation method developed in this thesis can provide a basis to help in negotiations between these stakeholders to determine the outcome measurements.

Implementation using a HIB will be hard as a complex network of actors with different incentives is involved. For example, health insurers are uncertain about the benefits of a HIB. These essential stakeholders are unsure about the actual savings, as a result of the implementation of the fall prevention programs, on the short- and long term. They expect that savings in the short term will be nullified by higher costs of care in the last year of the life of an elderly. In addition, they argue that any loss in revenue will be compensated by providing extra care in other departments of the hospital.

Apart from governance, some legal barriers need to be surmounted as health insurers and care offices cannot pay out possible health profits to private parties. Funds from the municipality through the WMO are not sufficient to cover the operational- and implementation costs of fall prevention programs. However, exceptions regarding this topic can be made by the ministry of VWS and they should facilitate that these exceptions are easily granted.

If these barriers can be overcome, a HIB can provide many opportunities to facilitate the implementation of programs in municipalities across the Netherlands which will improve the quality of life of elderly within Dutch society. By using this innovative structure, the financial risk of implementation is shifted from the local implementers to the investors, which encourages these implementers to develop and implement fall prevention programs. Moreover, as older adults are not required to pay for the fall prevention programs, they are more likely to participate. These two main advantages of HIBs might facilitate implementation in many regions across the Netherlands, resulting in a higher quality of life for older adults, and lower healthcare expenditures. However, only through open, sustained and coordinated efforts by both policymakers and stakeholders involved in elderly care, the HIB has a chance to become a leading instrument to implement fall prevention programs in the Netherlands.

9

Discussion and further research

It is often said that research leads to more questions than answers. Even though the findings of this research lead to new insights on the effectiveness of fall prevention programs, it is valuable to reflect on its limitations and possible further research.

The evaluation model developed during this research was designed to assess the effect of the fall prevention programs on both the number of injurious falls and the hospital expenditures. The DID design, to assess the effect of the programs on the hospital expenditures, proved to be unfit due to enormous differences in costs between the injuries caused by falls. The costs of the DOTs were known for some time and it could have been predicted that because of the small sample size, the trend would be influenced primarily by expensive femoral fractures.

However, in a few years from now, the fall prevention programs are expected to be implemented in the entire municipality of Dordrecht. Under the assumption that data will be available, a new control group can be chosen (with a similar SES-score as Dordrecht) and the method and evaluation tool from this research can be used to do the same case study only now with a larger dataset. The disruptive effect of the costly DOTs might be less and the CTA might hold. If so, the effect of the programs on hospital expenditures can be determined.

Other researchers could also help to improve the evaluation method further. This can be done by assessing the effectiveness of fall prevention programs in other areas. It is also possible to test the DID design to assess other outcome measures such as the effect of the programs on the number of deaths, operations, and hospital days, and the readmission rate. In addition, the model might be useful to assess other interventions to prevent falls. By using and adapting the model, incremental improvements can be made.

Currently, the evaluation model is fit to assess the effect of the programs on the number of injurious falls. However, a lot of adaptations are needed in order to create an evaluation model that meets the requirements so that it can be used in a HIB. The current model should be discussed with payers (municipalities, health insurers, care offices, and the government) in order to make improvements.

Another suggested study is to determine the additional benefits of fall prevention programs such as less informal care, less loneliness, or improvement of the quality of life. These benefits are largely unknown and are currently hard to monetize.

As this study has only explored the possibilities of a HIB, several recommendations for further research can be suggested. Firstly, ways how to remove governance- and legal barriers should be examined. Secondly, the (extra) organizational costs of a HIB should be estimated. Extra costs might be made to pay the independent assessor, for financial- and legal services or advice, and to pay the local implementor or intermediary. Thirdly, research should be done to examine which (legal) elements should be included. Firstly, ways how to remove governance- and legal barriers should be examined. Secondly, the (extra) organizational costs of a HIB should be estimated. Extra costs might be made to pay the

independent assessor, for financial- and legal services or advice, and to pay the local implementor or intermediary. Thirdly, research should be done to examine which (legal) elements should be included in a contract between the investors and payers and between investors and local implementers or executors. Finally, other types of outcome measures should be reviewed that can contribute to the fairness of the contract. For example, a HIB can be formed based on the results of a questionnaire. In this case, the investor is repaid based on, for example, the degree of loneliness of the elderly living in an area. This can be included in the contract between the investors and payers and between investors and local implementers or executors. Finally, other types of outcome measures should be reviewed that can contribute to the fairness of the contract. For example, a HIB can be formed based on the results of a questionnaire. In this case, the investor is repaid based on, for example, the degree of loneliness of the elderly living in an area.

However, the best way to really evaluate the applicability of a HIB is to set up a pilot project. The stepwise approach of the (concept) HIB described in section 7.2, can be used as a guideline to set up a HIB and elucidates on the requirements that need to be fulfilled to ensure a successful implementation. During such a project, it is imperative that all the aspects of the HIB will be evaluated before, during, and after this project to identify barriers and to improve the HIB concept.

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Appendices

Appendix A: Interviews

Appendix A1: Main conclusions multidisciplinary meeting (1)

Artsen van het Albert Schweitzer Ziekenhuis (ASZ), fysiotherapeuten (die valpreventieprogramma's aanbieden onder de naam Drechtmax) en ik zijn samengekomen voor een multidisciplinaire vergadering over valpreventie op 3 december 2018 in Dordrecht. De volgende personen waren aanwezig bij de vergadering:

- Annemarie van der Velden (SEH-arts in het ASZ & medisch manager van de SEH)
- Arno Hendriks (fysiotherapeut en eigenaar van fysiopraktijk Balanz & medeoprichter van DrechtMax en valpreventieprogramma's)
- Marcel van Houten (Werkzaam als geriatrie fysiotherapeut bij fysiopraktijk Crabbehof & medeoprichter valpreventie programma's & voorzitter van de ouderencommissie van FysioDordt)
- Marieke Meinardi (Internist ouderengeneeskunde op het ASZ)
- Joost van Berckel (TU Delft student met als afstudeeronderwerp 'Valpreventie')

Hieronder beschrijf welke problemen vallende ouderen veroorzaken en welke barrières er zijn voor het opzetten en uitvoeren van valpreventieprogramma's.

- ❖ De participatie van ouderen bij de valpreventieprogramma's kan worden verhoogd. Dit zijn de meest voorkomende barrières.
 - Voor de fysiotherapeuten is het lastig om in contact te komen met ouderen.
 - Ouderen, die te ver weg wonen van een praktijk die valpreventieprogramma's aanbiedt, kunnen daar vaak niet op eigen houtje komen. Ze moeten worden opgehaald met bijvoorbeeld een busje. Dit kost geld en gebeurt op dit moment nog niet.
 - Er worden te weinig ouderen doorverwezen naar fysiotherapeuten vanuit SEH- of Geriatrie afdeling. Op dit moment wordt er in het ziekenhuis wel fysiotherapie aangeraden, maar vervolgens vergeten de ouderen of zien niet de toegevoegde waarde hiervan in. Idealiter zou zijn dat de fysiotherapeuten langsgaan bij ouderen thuis. Daarvoor moeten de ziekenhuizen deze patiënten doorgeven aan de fysiotherapeuten via een systeem of een centraal callcenter. Deze mogelijkheden zijn er echter nog niet. Indien dit systeem er wel is, dan kunnen fysiotherapeuten langskomen bij een ouder persoon die zojuist is gevallen (en door het ziekenhuis is doorgegeven) om ze te screenen en ook valpreventieprogramma's aan te bieden.
 - Meedoen aan valpreventieprogramma's kost de ouderen geld. Sommige zorgverzekeraars vergoeden een deel van de kosten, anderen vergoeden niets. Hierdoor haken veel ouderen af.
 - Fysiotherapeuten van DrechtMax krijgen vanaf 2018 30.000 euro per jaar van de gemeente om onkosten te vergoeden. Er is meer geld nodig, mogelijk ook van andere stakeholders (zorgverzekeraar etc.).
- ❖ Wanneer alle vallende ouderen zouden meedoen met de huidige valpreventieprogramma's, dan hebben de fysiopraktijken te weinig capaciteit.
- ❖ Het huidige geriatrie netwerk bestrijkt nu een te groot gebied (Zuid-Holland Zuid) en daardoor verloopt de communicatie moeizaam. Het zou handiger zijn als het gebied wordt beperkt tot de invloedsfeer van het Albert Schweitzer Ziekenhuis (de Drechtsteden).

- ❖ Op dit moment is het alleen mogelijk voor geriatrie-fysiotherapeuten om zich bij het geriatrie netwerk aan te sluiten. Door meer disciplines te betrekken kan het voorkomen van valincidenten op een meer georganiseerde manier gebeuren.
- ❖ Er zijn geen flowcharts voor het behandelen van ouderen wanneer ze zijn gevallen. Het zou handig zijn om twee flowcharts te maken: 1) een overzicht van wat er met patiënten gebeurt vanaf dat ze op het ziekenhuis komen tot wanneer ze bij een fysiotherapeut terecht kunnen en 2) een overzicht dat laat zien wat er met de kwetsbare ouderen gebeurt vanaf het moment dat de ouderen bij de fysiotherapeut zijn en daarna.

Appendix A2: Main conclusions from orientation days

Appendix A2.1: Main conclusions from orientation day at Emergency Department

Ter oriëntatie heb ik een dag meegelopen op de Spoed Eisende Hulp (SEH) op 25 januari 2019. Hier belanden ouderen die (hard) zijn gevallen. Gedurende deze dagen heb ik veel medewerkers gesproken van meerdere disciplines binnen het ASZ en heb ik ook veel patiënten gesproken.

- ❖ De SEH wordt overspoeld met vallende ouderen (15-30 per dag).
- ❖ Overgroot deel van ouderen gaat naar huis na een valincident (80%), maar heeft een grote kans om opnieuw te vallen.
- ❖ Een deel hiervan gaat naar het Zorgtransferium. (Soort tussenoplossing: patiënt heeft geen operatie nodig, maar is te zwak om naar huis te gaan. Of: patiënt heeft een operatie gehad en is te zwak om naar huis te gaan óf heeft intensieve begeleiding nodig na een operatie om te herstellen).
- ❖ Deel van de gevallen ouderen worden opgenomen in ziekenhuis. De patiënt is dan te zwak om naar huis te gaan (en geen plek in het zorgtransferium) of heeft een operatie nodig. Na een opname in het ziekenhuis zijn ouderen doorgaans zwak en verliezen hierdoor een groot deel van hun zelfstandigheid. De kans dat zij opnieuw vallen is erg groot.
- ❖ Valincidenten (en de bijbehorende problemen) bij ouderen komen voor gedurende de hele week. Dus ook in het weekend. Er zijn op die tijden weinig mensen beschikbaar op de SEH, geriatrie of bij wijkverpleegkundigen. Het helpen van deze ouderen verloopt dan moeizaam.

Appendix A2.2 Main conclusions from orientation day at Geriatric Department

Daarnaast heb ik een dag meegelopen op de valpoli van de Geriatrie afdeling van het ASZ op 6 december 2018. Hier worden ouderen volledig gescreend op verschillende manieren en wordt er gekeken hoe het valrisico van een individuele oudere kan worden verlaagd.

- ❖ Medewerkers op de Geriatrie afdeling zijn niet op de hoogte van de valpreventieprogramma's.
- ❖ Veel ouderen zijn eenzaam en ongelukkig.
- ❖ Ouderenvallen vaak. Veel van hen ontkennen dat dit gebeurt.
- ❖ Veel ouderen komen niet in aanraking met ziekenhuizen of andere instanties. Hierdoor komen mensen, die werken in de zorgsector, er pas laat achter dat deze ouderen hulp nodig hebben. Het eerder opsporen van deze ouderen zou veel leed kunnen voorkomen.
- ❖ De thuissituatie is erg belangrijk voor het aantal valincidenten (kleedjes etc.). Het is vaak erg vies bij ouderen die alleen thuis wonen. Dit zorgt er ook voor dat ze vallen.
- ❖ Soms wordt er pas na dagen ontdekt dat er een oudere is gevallen in zijn eigen huis.
- ❖ Zicht van ouderen is vaak slecht.
- ❖ Geheugen is slecht (dementie etc.).
- ❖ Veel ouderen hebben oude versleten spullen aan (schoenen, steunkousen etc.). Hierdoor vallen ze sneller.
- ❖ Ouderenvallen kunnen erg koppig zijn en vinden doorgaans dat het allemaal wel goed gaat.
- ❖ Door deze koppigheid willen ze geen hulp(materiaal) (rolstoel, rollator etc.). Ook willen ze liever geen geld uitgeven (volgens geriater: de zuinige tweede wereldoorlog generatie).
- ❖ De kans op letsel neemt sterk toe met de leeftijd.
- ❖ Ouderenvallen in veel verschillende omgevingen en in alle seizoenen. Er vallen echter beduidend meer ouderen in de herfst (natte bladeren) of in de winter (glad). Ook geven een aantal ouderen aan dat er scheve stoepen zijn in Dordrecht waardoor zij hun evenwicht verliezen.

Appendix A3: Interview (1) with Emergency-physician Annemarie van der Velden

Het interview vond plaats op 29 januari 2019 in het Albert Schweitzer ziekenhuis en had de volgende doelen:

- ❖ Problematiek van vallende ouderen beter begrijpen
- ❖ Problemen identificeren rondom vallende ouderen (en mogelijke oplossingen bedenken)
- ❖ Selecteren van juiste diagnoses die te maken hebben met valincidenten
- ❖ Classificeren van de DBC's (zwaarte van letsel door valincidenten)

Het interview bestaat uit twee delen. De eerste gaat over de algemene problematiek van valincidenten en over problemen rondom het succesvol opzetten en uitvoeren van valpreventieprogramma's. Het tweede gaat over het begrijpen en valideren van de ziekenhuisdata van het Albert Schweitzer Ziekenhuis.

Appendix A3.1: General questions about falls in the elderly and what the barriers are to successfully implement fall prevention programs

1.1 Wordt er in Dordrecht veel aandacht besteed aan valpreventie?

Dat weet mevrouw van der Velden niet. Zij is gespecialiseerd in het behandelen van ouderen die al zijn gevallen op de spoedeisend hulp. Wel weet ze dat er een goed netwerk is van fysiotherapeuten, ergotherapeuten, geriaters en wijkverpleegkundigen die samenwerken om valincidenten tegen te gaan.

1.2 Was u op de hoogte van de valpreventieprogramma's in Dordrecht voordat u de vraag van meneer Hendriks (van Drechtmix) kreeg om een keer een vergadering te houden over valpreventie? Tijdens mijn meeloopdagen op de valpoli van de Geriatrie afdeling en op de SEH-afdeling viel het mij namelijk op dat medewerkers op deze beide afdelingen niet op de hoogte waren van de programma's.

Nee, mevrouw van der Velden was niet op de hoogte van deze valpreventieprogramma's. Voor de vergadering heeft ze intensieve brainstormsessies gehad met Internist Ouderengeneeskunde Marieke Meinardi over mogelijkheden om het aantal valincidenten terug te dringen. Ook met het idee om de druk van de SEH af te halen. Mevrouw Meinardi is vervolgens op zoek gegaan naar initiatieven in Dordrecht om het aantal vallende ouderen terug te dringen. Zo is zij bij meneer Hendriks terecht gekomen.

1.3 Welke maatregelen neemt het ASZ tegen vallende ouderen? Wat is de rol van de SEH hierin?

De SEH doet hier weinig mee. De Geriatrie afdeling focust hier meer op. Hier wordt er met name gekeken of een oudere (een combinatie van) medicijnen slikt die ervoor kunnen zorgen dat een oudere instabiel wordt. De artsen op deze afdeling kunnen dan vervolgens besluiten het medicijngebruik terug te dringen, of het type medicijn te veranderen.

1.4 Wat zijn volgens u de belangrijkste barrières voor het terugdringen van het aantal valincidenten? Ik zou graag nog even de lijst met problemen willen doorlopen die ik heb opgeschreven tijdens de vergadering met meneer Hendriks, meneer van houten, mevrouw Meinardi en met u op maandag 3 december (zie paragraaf 1.1).

Volgens mevrouw van der Velden is dit inderdaad een goede lijst met barrières voor het voorkomen van valincidenten. Er werden veel voorbeelden gegeven van patiënten die inderdaad keer op keer door een val op de SEH komen. De SEH-artsen zitten doorgaans met de handen in het haar wanneer er een patiënt

voor de zoveelste keer op de SEH komt en het is lastig te concluderen dat af en toe niet echt een oplossing is voor deze gevallen.

1.5 Wat gebeurt er doorgaans met ouderen die zijn gevallen? Na een val komen de ouderen zelf of per ambulance op de SEH terecht. Op de vorige vergadering heb ik gehoord dat 80% naar huis gaat met een kleine verwonding, dat 15% wordt geopereerd en ongeveer 5% naar het zorgtransferium gaat. Klopt dit ongeveer?

Er vallen inderdaad ongeveer 15 ouderen per dag. Dit is ook sterk afhankelijk van het weer en ook seizoenen spelen een belangrijke rol. Per dag zijn er doorgaans 1 of 2 gebroken heupen.

Het zorgtransferium is een tussenoplossing voor mensen waarbij het net niet meer gaat. Een voorbeeld hiervan is bijvoorbeeld dat een ouder persoon zijn of haar pols breekt. Deze mensen kunnen niet meer met een rollator lopen, dus diegene kan eigenlijk niet meer lopen. Er moet constant iemand zijn die deze oudere persoon begeleid. Deze ouderen gaan dus naar het Zorgtransferium. Hier liggen ze 24 uur en dan de volgende ochtend wordt er dan een plek in een verpleeghuis geregeld via de geriater. Hier wordt er dan geoefend met een fysiotherapeut.

1.6 Op welke manier zouden alle partijen, die met de zorg voor (kwetsbare) ouderen te maken hebben, beter kunnen samenwerken om ervoor te zorgen dat er meer aandacht komt voor valpreventieprogramma's?

Mevrouw van der Velden is niet goed op de hoogte van het beleid van verpleeghuizen. Wel denkt ze dat de verplegers, die intensief met een ouder persoon optrekken, goed zicht hebben op wat een ouder persoon nodig heeft. Zij kunnen dan besluiten of er juist krachtoefeningen nodig zijn, of juist balans oefeningen. Mevrouw Meinardi (internist ouderengeneeskunde) zal hier meer over weten. Om een echt goed beeld te krijgen zou ik de specialist ouderengeneeskunde moeten benaderen die actief is buiten het ziekenhuis in één van de verwijzende verpleeghuizen met grote revalidatie unit.

1.7 Kan ik u nog helpen met de actiepunten voor de volgende valpreventievergadering in februari (met meneer Hendriks, meneer van houten, mevrouw Meinardi en met mevrouw van der Velden)?

Mevrouw van der Velden heeft aangegeven het fijn te vinden dat ik ga onderzoeken hoeveel ouderen er per jaar vallen in Dordrecht. Daarna kunnen we samen de cijfers controleren door nogmaals data uit het systeem te halen met het doel om deze dan 'grof' met elkaar te vergelijken. Hierover zal mevrouw van der Velden nog contact met mij opnemen.

Appendix A3.2: Questions about analysing the hospital data

2.1 Ik heb meegemaakt dat het hectisch kan zijn op de SEH. Ik kan me voorstellen dat het lastig is om alle DOT's op een juiste manier in te voeren. In hoeverre denk je dat de DOT-data op een juiste manier in het systeem wordt gezet?

De DOT's worden over het algemeen heel goed in het systeem gezet. Eerst wordt dit door artsen of arts-assistent gedaan aan het eind van een dienst in alle rust. Dezelfde dag of een dag later worden deze gegevens nog gecontroleerd door secretaresses. Er zit een heel systeem achter om ervoor te zorgen dat de DOT wordt geregistreerd.

Vaak worden er eerst 'Dummy' DOT's aangemaakt (een DOT zonder beschrijving), zodat alle verrichtingen kunnen worden geregistreerd. Later wordt er dan de juiste DOT aan gekoppeld.

Er wordt standaard gevraagd aan een patiënt: "werd u onwel?" of "Bent u gestruikeld?". Wanneer een patiënt onwel is geraakt, dan krijgt diegene een andere DOT (bijvoorbeeld beroerte) dan bij een valincident.

2.2 Is er veel variatie tussen seizoenen?

Ja, er is zeker een patroon per seizoen. Ook jongere mensen vallen een stuk vaker als er bijvoorbeeld ijs ligt. Echte ijsdagen kan je terugzien, want dan is er een enorme piek te zien qua DBC's van de chirurgie. Het type letsel is dan ook doorgaans anders.

Mevrouw van der velden zegt dat het verstandig is om alle periodes wel mee te nemen in het dataonderzoek, omdat het toch een seizoenspatroon is. Ook als je namelijk fitter bent of een valpreventieprogramma hebt gevolgd, dan is de kans kleiner dat je valt en ook een stuk kleiner dat je op je heup valt. Het feit dat je op je heup valt betekent dat je al langer achteruitgaat. Helaas is na 2 jaar al 70 procent van de ouderen boven de 75 overleden na een val op de heup. Na 5 jaar zijn ze bijna allemaal overleden. Met uitzondering van de 'jonge' ouderen (net boven de 65).

2.3 Is het met grote zekerheid te zeggen dat als deze letsels bij ouderen worden geconstateerd en geregistreerd, dat het dan gaat om een valincident en bijvoorbeeld niet om een auto-ongeluk?

Met grote zekerheid is te zeggen dat de overgrote groep van deze DBC's te maken hebben met vallen. Heupfracturen krijg je niet van auto-ongelukken. Natuurlijk zijn er uitzonderingen, maar volgens mevrouw van der Velden gaan die gevallen zeker niet deze data 'vertroebelen'. Zware auto-ongelukken gaan doorgaans naar het Erasmus MC in Rotterdam.

2.4 Zijn er nog andere ziekenhuizen of andere instellingen waar een oudere terecht kan na een val? Of komt nagenoeg iedere oudere na een valincident naar het Albert Schweitzer ziekenhuis?

Hele kleine groep vallende ouderen zullen gaan naar het Erasmus, wanneer er bijvoorbeeld blijkt dat er een zeer ernstige hersenbloeding gaande is bij een persoon. Dit zijn er erg weinig en je kan je ook afvragen hoe deze ouderen uit het ziekenhuis zullen komen (en of ze wel uit het ziekenhuis gaan komen). Volgens mevrouw van der Velden moet je je bij valpreventie niet richten op de ernstigste gevallen.

Nagenoeg elke oudere in Dordrecht komt na een valincident naar het Albert Schweitzer ziekenhuis. Er gaan enkele ouderen naar Zwijndrecht (1 a 2 per dag). Hier zit ook een kleine SEH. En dan zou het met name gaan om mensen met lichte fracturen. Wat je verliest is niet een groot percentage.

2.5 Ik heb met grondig onderzoek verschillende diagnoses geselecteerd, waarvan ik denk dat de oorzaak een valincident moet zijn geweest. Zijn deze DOT's allen gerelateerd aan vallende ouderen? Graag zou ik met u deze lijst (in Excel) willen doornemen.

Ja, de door jou gekozen diagnoses (fracturen) zijn voor het grootste deel gerelateerd aan vallende ouderen. Samen met mevrouw van der Velden zijn we een lijst met 73 diagnoses afgegaan met drie specialismen: Neurologie, Orthopedie en Heelkunde (Chirurgie). Hieronder zijn de belangrijkste notities per specialisme te vinden.

Neurologie

Twee diagnoses van Neurologie zijn de correcte diagnoses voor nagenoeg alle valincidenten op het hoofd. Er is slechts een klein groepje 'hoofd-vallers' waar een neuroloog niet bij is betrokken. Belangrijk om te kijken of er geen dubbele DBC is aangemaakt op dezelfde dag bij dezelfde patiënt.

Orthopedie

In principe gaan val-patiënten naar de chirurg, tenzij er iets heel specifieks aan de hand is. Dan worden de ouderen doorgestuurd naar de Orthopedie. Veel van deze fracturen, die worden behandeld door de

Orthoped, zijn zeer ingewikkeld. Het gaat vaak om een fractuur die te maken heeft met (gewricht)banden, óf het kan zijn dat er een prothese nodig is.

De ene week worden de heupoperaties gedaan door Orthopedisten, de andere week door chirurgen.

Behandelingen aan wervelkolommen worden ook gedaan door de Orthoped. Dit zijn jaarlijks veel ouderen en ook hier is het met grote zekerheid te zeggen dat een val de oorzaak is van de fractuur.

Heelkunde

Met grote zekerheid te zeggen dat ouderen met deze diagnoses zijn gevallen. Misschien zit er nog een klein deel in de plastische chirurgie, want die behandelen soms gebroken handen. Dit gebeurt slechts 1 keer per maand en is dus niet erg relevant voor mijn onderzoek.

Algemene notitie

De 80% procent (de mensen die dezelfde dag naar huis gaan, zie vraag 5) zit dus deels bij Contusies (kneuzingen), maar ook bij voorbeeld polsen die snel kunnen worden behandeld op dezelfde dag (met voorbeeld gips).

De reden dat de DOT 'contusie' zo duur is, is omdat er vaak ook foto's (X-ray en CT-scan) worden gemaakt. De 'lichte' vallers (waar niet zo veel aan de hand blijkt te zijn) krijgen doorgaans of een DOT bij 'Contusie' of bij 'Overig letsel hoofd'.

Nogmaals: let dus op dubbele DBC's, want het kan zijn dat er én een contusie DBC wordt aangemaakt én een DBC voor een fractuur. Als je je pols breekt en ook je enkel. Dan krijg je twee DOT's, omdat het beide verschillende behandel trajecten zijn.

Conclusie: Goede en complete lijst. De resultaten van mijn onderzoek ga ik doorsturen naar SEH-arts Annemarie van der Velden en zij zal een grove check doen of het klopt. Zij zal ook nog eens extra naar Zwijndrecht kijken (of daar toch nog ouderen komen die zijn gevallen).

2.6 Bijna alle diagnoses hebben de volgende onderliggende DBC's. Kunt u uitleggen wat dit betekent voor de ernst van het letsel? Onderstaand voorbeeld gaat over een polsfractuur.

- a. 3x ambulant (licht, middel, zwaar).
 - i. Poliklinisch. Ligt aan het aantal keer dat de patiënten terug moeten komen. Als ze 1 keer moeten terugkomen om het gips eraf te halen, dan is het bijvoorbeeld licht. Bepaalde breuken duren langer, en dan moet de patiënt ook meerdere keren terugkomen. Deze krijgen dan een 'middel'- of 'zwaar'-ambulante DOT.
- b. 3x klin (kort, middel, lang)
 - i. Klinisch kort is bijna hetzelfde als Oper bovenste extremiteit MET VPLD. Ligt aan het type operatie.
 - ii. Om een klinisch DOT te registreren, dan moet de patiënt minimaal een nacht in het ziekenhuis zijn verbleven. Af en toe wordt daar weleens mee gespeeld. Dan wordt er een operatie gepland om 5 uur en dan om 8 uur (na de operatie) wordt het advies van de chirurg om ook de nacht te blijven. Dan veranderd de DOT van een ambulante naar een klinische DOT en komt er meer geld binnen.
- c. Oper bovenste extremiteit MET VPLD
 - i. Gaat om een operatie.
 - ii. De verpleegdag kan te maken hebben met het tijdstip van opname. Het hoeft dus niet per se te maken te hebben met een zwaarder letsel. Wanneer een

patiënt binnenkomt ergens in de avond, dan wordt doorgaans de operatie uitgesteld tot de volgende dag.

- d. Oper bovenste extremiteit ZONDER VPLD
 - i. Gaat om een operatie.

Als je wordt geopereerd, dan zullen ook alle poliklinische bezoeken onder diezelfde DOT vallen.

Table 10: Possible DOTs in the event of a wrist fracture (example)

Diagnosis	Specialism	DOT product	Total costs ASZ	Cost per DBC
212, Pols	0303, Heelkunde	199299119, Letsel (excl heupfractuur) Ambulant middel Letsel overig	€ 297,618.11	€ 490.31
212, Pols	0303, Heelkunde	199299069, Oper bovenste extremiteit (excl hand) extra-articulair Zonder VPLD Letsel overig	€ 297,013.28	€ 3,622.11
212, Pols	0303, Heelkunde	199299118, Letsel (excl heupfractuur) Ambulant zwaar Letsel overig	€ 130,661.97	€ 859.62
212, Pols	0303, Heelkunde	199299070, Oper bovenste extremiteit (excl hand) extra-articulair Met VPLD Letsel overig	€ 82,655.04	€ 5,510.34
212, Pols	0303, Heelkunde	199299120, Letsel (excl heupfractuur) Licht ambulant Letsel overig	€ 34,690.02	€ 172.59
212, Pols	0303, Heelkunde	199299013, Letsel (excl heupfractuur) Klin kort Letsel overig	€ 24,083.98	€ 2,676.00
212, Pols	0303, Heelkunde	199299018, Letsel (excl heupfractuur) Klin middel Letsel overig	€ 13,586.38	€ 4,528.79
212, Pols	0303, Heelkunde	199299057, Oper huid/ weke delen overig middel Zonder VPLD Letsel overig	€ 1,403.87	€ 1,403.87
212, Pols	0303, Heelkunde	199299122, Uitval geen poli/ geen eenmalig traumatologisch consult Letsel (excl heupfractuur) Letsel overig	€ 1,254.54	€ 54.55
212, Pols	0303, Heelkunde	199299001, Uitval standaard Letsel overig	€ 232.52	€ 232.52

Appendix A4: Interview (2) with ER-physician Annemarie van der Velden

Het interview vond plaats op 26 februari 2019 in het Albert Schweitzer ziekenhuis en had de volgende doelen:

- ❖ Selecteren van juiste diagnoses die te maken hebben met valincidenten.
- ❖ Classificeren van de DBC's (zwaarte van letsel door valincidenten).
- ❖ Controleren en valideren van de data (na een snelle analyse in Excel).

Appendix A4.1: Questions about the selection and classifying of the relevant diagnoses related to fall incidents

1.1 Na het vorige interview heb ik de geselecteerde relevante diagnoses geclassificeerd op een schaal van 1 tot 6. Wat vindt u van de indeling? Zijn er diagnoses die niet de goede classificatie hebben gekregen?
Graag zou ik met u deze lijst (in Excel) willen doornemen.

Mevrouw van der Velden vond het over het algemeen een goede classificatie, maar heeft een aantal aanpassingen gemaakt. Ik had bijvoorbeeld alleen 'Femur' en 'Femur overig' (heupfractuur) in de zwaarste classificatie (6) gezet, maar het blijkt dat er ook zeer ernstige gevolgen zijn bij het breken van je knie (patella en tibialplateau), scheenbeen (tibia) en gewricht bij je heup (Acetabulum). Deze DBC's (ten minste: de niet ambulante) hebben nu classificatie 6. Daarnaast zijn er nog een aantal diagnoses van categorie 4 naar 5 overgeplaatst en andersom.

Daarnaast bleek dat bij 'Femur' en 'Femur overig' ook de ambulante DBC's classificatie 6 horen te krijgen, omdat deze ouderen óf overlijden óf worden overgeplaatst naar een ander ziekenhuis. Bij de andere diagnoses, die onder de zware categorie 6 staan, wordt er wel redelijk vaak gekozen voor geen operatie en dus een ambulante behandeling. De ambulante DBC's van deze diagnoses (knie, scheenbeen, gewricht bij heup) zijn nu ingedeeld in categorie 3.

De Excel 'Selection relevant diagnoses and classification' is aangepast aan de hand van deze informatie. Gedetailleerde notities over de verschillende diagnoses staan in de kolom 'Notes' op tabblad 'A.2 Classification relevant DOT'.

1.2 Na het vorige interview ben ik nog een aantal diagnoses tegengekomen in de data waarvan het misschien nog mogelijk is dat de oorzaak een valincident is. Zijn deze DOT's gerelateerd aan vallende ouderen? Graag zou ik met u deze lijst (in Excel) willen doornemen.

Van deze 'extra' lijst met diagnoses die door vallen komen, zijn er slechts 2 die worden veroorzaakt door valincidenten (zie rijen 96 tot 112). Deze worden toegevoegd aan de analyse. Het gaat echter niet om veel DOT's en daarom zal het geen grote invloed hebben op de resultaten.

Bij een aantal van deze diagnoses is het mogelijk dat er een aantal worden veroorzaakt door een valincident, maar dat het niet te bepalen is welke. Daarnaast zijn deze DOT's dan ook vaak gekoppeld aan een andere DOT van de Neurologie, zoals de DOT 'Overig letsel hoofd' of 'Contusio / commotio cerebri'. Deze worden als meegenomen in de analyse.

De Excel 'Selection relevant diagnoses and classification' is aangepast aan de hand van deze informatie. Gedetailleerde notities over de verschillende diagnoses staan in de kolom 'Notes' op tabblad 'A.1 Selection relevant diagnose'.

Appendix A4.2: Questions with the goal to check and validate the data

2.1 U zei in de vergadering dat er ongeveer 10-15 ouderen per dag op de SEH komen die zijn gevallen. Volgens deze eerste (snelle) analyse zijn er gemiddeld 6-7 ouderen. Kloppen deze uitkomsten? Of mist er nog een groep patiënten?

Er mist nog een groep ouderen die zijn gevallen en waarvan wordt gedacht dat zij ‘onwel’ zijn geworden, maar dat niet zijn. De ouderen die op de SEH komen en zijn gevallen krijgen de vraag of ze ‘onwel’ zijn geworden of ‘uit balans’ zijn geraakt. Vaak weten de ouderen dit niet meer en moet er een lastige inschatting worden gemaakt door de arts. Als er een vermoeden is dat zij ‘onwel’ zijn geworden, dan kunnen ze naar verschillende afdelingen worden gestuurd om de oorzaak daarvan te achterhalen. Zo kunnen deze ouderen bij de Neurologie afdeling komen en de diagnose ‘Collapse’ krijgen (in totaal 700 DBC’s geschreven in de laatste 5 jaar).

Ook worden deze patiënten doorgestuurd naar de Cardiologie afdeling voor een controle van het hart. Er is dus een groep ouderen die volledig worden gescreend, maar dat er geen oorzaak wordt gevonden. Als er geen oorzaak is gevonden, zou je kunnen zeggen dat ze ‘gewoon’ gevallen zijn, omdat ze niet stabiel/fit genoeg zijn. Het is echter niet te bepalen welke patiënten dit zijn, omdat ze zijn uitgesmeerd over een groot aantal DBC’s. Kortom: het is dus erg lastig deze patiëntenpopulatie te vinden, want het is een hele heterogene groep. Daarom is het niet mogelijk de DBC’s mee te nemen in de analyse.

In mijn onderzoek zal ik mij dus focussen op de ouderen die een (zichtbaar) letsel hebben opgelopen. Mevrouw van der Velden heeft er veel vertrouwen in dat de geselecteerde diagnoses correct zijn om deze patiëntenpopulatie te onderzoeken. Als er namelijk significant letsel geconstateerd wordt, dan wordt ook altijd de chirurg erbij betrokken en dat wordt dan ook geregistreerd (en meegenomen in de analyse).

2.2 Het valt op dat er in 2018 minder ‘Commotio / contusio cerebri’ DBC’s zijn, en meer ‘overig letsel hoofd’. Is er iets aan de manier van registreren veranderd in 2018?

Voor een ‘Commotio / contusio cerebri’ moet er op de CT-scan een bloeding te zien zijn. Dit kan per jaar wat verschillen. Verder is in september 2017 het nieuwe HiX-systeem geïmplementeerd, maar dat zou niet moeten uitmaken. Wel kan het zijn dat er nog een deel van de DBC’s worden gecontroleerd door de financiële afdeling in het ziekenhuis en dat deze dan nog kunnen worden aangepast. Dit zou dan voornamelijk moeten gelden voor de maand december.

2.3 Er zijn weinig gekoppelde DBC’s te vinden (aangegeven met een Q), terwijl u het vaak heeft over gekoppelde DBC’s. Hoe kan dit?

De financiële afdeling gaat vaak nog maanden na het registreren van de DBC’s de gehele lijst langs en verandert vaak een gekoppelde DBC in een reguliere DBC.

2.4 Is er al meer duidelijkheid over het aantal vallende ouderen dat op de SEH komt van Zwijndrecht?

Deze cijfers heeft mevrouw van der Velden nog niet. Ze verwacht dat dit er weinig zullen zijn. Er komen bijvoorbeeld in totaal 40.000 mensen (van alle leeftijden) op de SEH op het ASZ in Dordrecht per jaar en slechts 2.800 mensen per jaar op de SEH-post in Zwijndrecht. Als er iets ernstigs aan de hand is, dan komen ze alsnog naar het ASZ (bijvoorbeeld een heupbreuk). Personen met kleinere letsen kunnen wel bij de SEH-post in Zwijndrecht.

2.5 Ik heb ook gegevens over de datum van overlijden van de patiënten. Graag zou ik willen onderzoeken of er door valpreventieprogramma's minder ouderen overlijden. Als een patiënt bijvoorbeeld binnen 3 maanden overlijdt na een val, is er dan een grote kans dat de val indirect de doodsoorzaak is?

Er is zeker een grote kans dat het overlijden indirect komt door een val, maar het is erg lastig iets te zeggen over de periode waarin je dan moet kijken.

Het feit dat je op je heup valt betekent dat je al langer achteruitgaat. In de literatuur kan je hier meer over lezen. Deze ouderen zijn dan gevallen door al een verslechterde conditie en overlijden vaak ook daarna. Je gaat dus niet per se dood, omdat je je heup breekt. Je gaat dood, omdat je slechter wordt en daardoor je heup breekt. Helaas is na 2 jaar al 70 procent van de ouderen boven de 75 overleden na een val op de heup. Na 5 jaar zijn ze bijna allemaal overleden. Met uitzondering van de 'jonge' ouderen (net boven de 65).

2.6 Het is opvallend dat van de ongeveer 12.000 ouderen (die zijn gevallen) er slechts 4.800 komen uit de stad Dordrecht. De rest komt uit andere steden en dorpen in de regio. Kan dit kloppen?

Ja, dit klopt zeker! Ik zal je laten zien uit welke regio's mensen komen (laat op Google Maps het gebied zien: groot deel van Zeeland, tot boven Breda, tot onder Rotterdam, tot tegen Gorinchem). Mensen uit Puttershoek komen hier ook allemaal heen en in Zuid-Beijerland staat nog een ambulancepost die rechtstreeks naar het ASZ gaat. De post Spijkenisse is in de nachts dicht, dus dan gaan mensen óf naar Rotterdam óf naar Dordrecht (kan relevant zijn als de controlegroep niet groot genoeg is).

2.7 Algemene notities tijdens het interview.

- Je kan je afvragen of je er goed aan doet alle nuances in het onderzoek mee te nemen. Ik (mevrouw van der Velden) denk van wel. Ik denk dat je op deze manier betere getallen krijgt.
- Het beste zou zijn als je al met de ouderen aan de slag kan, wanneer ze nog geen letsel hebben opgelopen. Dit is erg lastig (meneer Hendriks weet hier meer over).
- Mevrouw van der Velden denkt niet dat vrouwen relatief vaker vallen dan mannen. Vrouwen worden over het algemeen ouder en dus worden er ook meer vrouwen opgenomen na een valincident.
- In de data staan gegevens over de ouderen of ze van een verzorgingstehuis komen of vanuit huis. Dit wordt niet altijd goed geregistreerd. Wat handig is om te doen: zoek op waar de verzorgingstehuizen (of verpleeghuizen) in Dordrecht staan en koppel deze met de data. Dit beïnvloedt het aantal bejaarden en het aantal mensen dat er slecht aan toe is (hier kan ook eventueel een controlevariabele voor worden toegevoegd). Daarnaast zijn er ook aanleunwoningen die gekoppeld zijn aan een VVT-instellingen. Dit is een soort tussenvorm.
- Over het algemeen heeft mevrouw van der Velden wel vertrouwen in de cijfers en herkent ze ook de aspecten die we hebben besproken. Op 19 maart is er opnieuw een vergadering met Annemarie van der Velden, Arno Hendriks, Marieke Meinardi en Marcel houten.

Appendix A5: Interview with Physiotherapist Arno Hendriks

Ik heb een interview gehouden op 11 maart 2019 met Arno Hendriks. Hij is eigenaar van fysiotherapiepraktijk ‘Balanz’ in Dordrecht en hij heeft Drechtmax opgezet. Ik heb hem eerder gesproken op de vergadering van 3 december (Hendriks et al., multidisciplinary meeting 1, 2018).

Het interview had de volgende doelen:

- ❖ Informatie inwinnen over de kosten van de valpreventieprogramma’s.
- ❖ Duidelijkheid krijgen over de begin- en einddatums van de verschillende valpreventieprogramma’s bij de verschillende fysiotherapiepraktijken.
- ❖ Problematiek van vallende ouderen beter begrijpen.
- ❖ Problemen identificeren rondom vallende ouderen (en mogelijke oplossingen bedenken).
- ❖ Haalbaarheid van Health Impact Bond evalueren.

Het interview bestaat uit drie delen. Het eerste deel gaat over de algemene problematiek van valincidenten (in Dordrecht) en over problemen rondom het succesvol opzetten en uitvoeren van valpreventieprogramma’s. Het tweede deel bevat vragen met betrekking tot het onderzoek naar de effectiviteit van de programma’s. Het laatste deel bevat vragen met betrekking tot de haalbaarheid van een health impact bond.

Appendix A5.1: Questions about the barriers to implement fall prevention programs

1.1 Waarom bent u begonnen met het bedenken en opzetten van valpreventieprogramma’s?

Het is begonnen toen ik (Arno) een brief ontving van de gemeente in 2014. Zij wilden graag weten hoe het gesteld is met de kwetsbaarheid onder ouderen in Dordrecht. Op hun verzoek hebben ik in samenwerking met onder andere Marcel van Houten een aantal tools gemaakt om dit te gaan bepalen. We hebben toen een aantal fysieke tools gemaakt en ook een aantal vragenlijsten opgesteld, zodat we ouderen op hun kwetsbaarheid op een goede wijze konden screenen.

Toen hebben we 2.100 ouderen in Dordrecht benaderd, waarvan er toen 1.200 zich hebben aangemeld. In 2014 en 2015 hebben we toen 1.200 ouderen gescreend. Van die ouderen bleek 8% kwetsbaar en daarnaast bleek dat er een grote groep (52%) van de ouderen eenzaam was, waarvan ook een deel ernstig eenzaam (12%). Van dit onderzoek is een document gemaakt. Dit zal ik je opsturen.

Voor het screenen is er twee keer 26.000 euro beschikbaar gesteld door de gemeente. Het kostte erg veel tijd en geld. De gemeente heeft dus een deel van deze kosten vergoed, maar zelf heb ik ook veel tijd in dit onderzoek gestoken zonder dat ik daarvoor iets heb gekregen. Dit kwam omdat er veel meer mensen zich hadden aangemeld dan vooraf was gedacht. Dit was mijn eigen keuze.

De gemeente heeft de resultaten, die ik je zal opsturen, bekeken en heeft toen ingezien dat dit een groot probleem is in Dordrecht. Zij wilden graag dat er een oplossing kwam. Daarom zijn deze vitaliteits- en valpreventieprogramma’s bedacht en opgezet. Het doel van deze programma’s zou zijn om het valrisico terug te dringen, zodat ouderen voor een langere tijd zelfstandig thuis zouden kunnen blijven wonen. Daarnaast zouden deze programma’s zorgen voor minder eenzaamheid onder ouderen. De gemeente wilde graag dat er werd gefocust op de gebieden waar de vergrijzing het grootst is: namelijk in Dordrecht-Oost. Daarom zijn we ook daar begonnen. De gemeente heeft 25.000 euro subsidie gegeven voor het opzetten en uitvoeren van de programma’s in het eerste jaar (2017). Dit bleek ook niet genoeg. Ook dit heb ik opgelost door flink wat uren gratis te werken, zodat de begroting ongeveer klopte. Ik wilde namelijk wel dat het een succes werd.

Door het succes in 2017, is er besloten dat de gemeente vanaf 2018 elk jaar 30.000 euro beschikbaar stelt om de programma’s te laten lopen. Een hoger bedrag zal zeker helpen om het aantal participanten te verhogen. Het doel van de komende jaren is om deze programma’s overall in Dordrecht te kunnen aanbieden.

De begroting van de verschillende jaren zal ik je opsturen. Een subsidie is vaak als volgt opgebouwd. Je krijgt de subsidie afhankelijk van het aantal deelnemers je denkt te behalen. Van deze deelnemers krijg je ook inkomsten. De subsidie die je krijgt is vaak de inkomsten minus de totale kosten voor het geven van de programma's. Zelf ben ik vrij onervaren in het aanvragen van subsidies. Ik denk dat we met meer geld meer kunnen doen.

1.2 Wordt er in Dordrecht veel aandacht besteed aan valpreventie in vergelijking met andere steden? Welke maatregelen neemt de gemeente?

De gemeente van Dordrecht doet relatief veel aan valpreventie. Dit is dan ook het 3^e jaar op rij dat zij 25.000 euro, 30.000 euro en 30.000 euro aan subsidie geven om de valpreventieprogramma's van Drechtnet te ondersteunen. Ze vinden het belangrijk om het steeds stijgende aantal vallende ouderen terug te brengen. Daarnaast is de GGD bezig met een integrale aanpak van valpreventie met meerder e stakeholders (ergotherapeuten, huisartsen, fysiotherapeuten, artsen, sociaal wijkteam etc.).

Volgens meneer Hendriks zouden zij (de GGD) kunnen helpen om een beter doorverwijssysteem (besproken in Interview in Hendriks et al., multidisciplinary meeting 1, 2018) op te zetten om ouderen met een hoog valrisico door te verwijzen vanaf (de SEH van) het ASZ naar de fysiotherapiepraktijken. Op deze manier zullen er meer mensen meedoen met de vitaliteits- en valpreventieprogramma's. Het probleem is echter ook, dat als het aantal deelnemers stijgt, dat dan ook de capaciteit van de programma's omhoog moet. Hier is geld voor nodig, wat er op dit moment niet is.

1.3 Wat zijn volgens u de belangrijkste barrières voor het terugdringen van het aantal valincidenten?

Hieronder heb ik opgeschreven wat tijdens de vergadering op 3 december werd gezegd (met meneer van houten, mevrouw Meinardi, Annemarie van der Velden). Mis ik nog belangrijke andere factoren?

1. *Participatie van ouderen kan hoger. Dit zijn de belangrijkste barrières voor ouderen om mee te doen met de programma's:*
 - a. *Lastig om in contact te komen met de ouderen. Veel betrokken actoren zijn niet op de hoogte dat deze programma's er zijn en verwijzen hun patiënten ook niet door. Een callcenter of een systeem (met doorverwijsformulier) ontbreekt nog.*
 - b. *Het kost ouderen geld om mee te doen met de programma's*
 - c. *Ouderen wonen te ver weg en kunnen niet op eigen houtje komen naar de praktijken die valpreventieprogramma's aanbieden.*
 - d. *De huidige capaciteit van de deelnemende fysiotherapiepraktijken is te laag.*
2. *Het geriatrinenetwerk bestrijkt een te groot gebied*
3. *Niet iedereen kan zich aansluiten bij het geriatrinenetwerk*
4. *Er is niet genoeg geld beschikbaar om op grote schaal valpreventie te implementeren.*
5. *Er is onduidelijkheid over de rolverdeling. Een flowchart ontbreekt.*

Dit rijtje klopt zeker. Zoals eerdergenoemd zou een oplossing kunnen zijn om een systeem op te zetten om patiënten door te verwijzen van het ASZ naar de fysiotherapiepraktijken. Ook zou het mooi zijn als er, na een bezoek bij de SEH, een 'toestemmingsformulier' wordt ingevuld door de patiënt. Dit zal nodig zijn, zodat het ziekenhuis toestemming heeft om de contactgegevens van een patiënt door te geven aan een fysiotherapiepraktijk, zodat zij de patiënt kunnen benaderen voor een valpreventieprogramma. Daar komt nog bij dat het lastig is om huisartsen te betrekken. Zij zouden een grote centrale rol kunnen spelen in het doorverwijzen.

Daarnaast is er te weinig geld beschikbaar om deze valpreventieprogramma's op een grotere schaal aan te bieden in Dordrecht.

1.4 Tijdens de vorige meeting had u het erover dat u een flowchart zou maken over wat er met ouderen gebeurt als ze van de Spoedeisende Hulp (SEH) komen. Heeft u deze flowchart gemaakt? Zelf heb ik zeer globaal een flowchart gemaakt met de belangrijkste partijen en vanuit welke situatie ouderen terecht zouden kunnen komen bij uw valpreventieprogramma's. Klopt dit beeld?

Ik denk dat dit beeld wel ongeveer klopt, maar dit is iets waar ik weinig zicht op heb. Volgende week op de vergadering van 19 maart (met dezelfde personen als bij interview 1), zal het duidelijk worden hoe we de samenwerking onderling beter kunnen regelen.

1.5 Het beste zou zijn als je met de ouderen aan de slag kan, wanneer ze nog geen letsel hebben opgelopen door een valincident. Mevrouw van der Velden gaf al aan dat dit erg lastig is. Doen er ouderen mee die nog geen letsel hebben opgelopen en deelnemen om te voorkomen dat ze ooit een val maken met grote consequenties? Hoe kan de participatie van deze groep ouderen worden verhoogd?

Ja, er doen zeker ouderen mee die willen voorkomen dat ze ooit een grote smak maken, maar het is lastig om deze groep te bereiken. Tot nu toe proberen we met deze mensen in aanraking te komen door folders over deze programma's te verspreiden en daarnaast vertellen we over de programma's aan ouderen die langskomen op onze praktijk. Dit gebeurt ook in alle andere (13) betrokken praktijken. Er zijn ook veel advertenties geplaatst over de programma's en we zijn ook een aantal keer in de krant gekomen.

We hebben helaas weinig contact met huisartsen, want deze zijn vaak erg druk. Via hen zouden we met veel ouderen (met een verhoogd valrisico) in contact kunnen komen.

De GGD is bezig met het ontwikkelen van een integrale aanpak voor valpreventie. Zij gaan binnenkort een bijeenkomst organiseren met de betrokken partijen om ervoor te zorgen dat we beter en effectiever samen gaan werken.

1.6 In de andere wijken van Dordrecht zijn ook fysiotherapiepraktijken te vinden. Doen deze ook (actief) iets aan vitaliteits- en valpreventieprogramma's? Zo ja, welke programma's? En welke bieden dit aan?

Nee, voor zover ik weet worden in die praktijken geen programma's aangeboden. Als het zo was, had ik het zeker geweten.

Verder valt het ons op dat er ook twee fysiopraktijken uit de wijk Crispijn hebben meegedaan met de programma's, maar dat daar geen enkele oudere heeft meegedaan. Daarom doen die praktijken ook niet meer mee dit jaar. Het blijft erg eigenaardig. Dit kan aan verschillende zaken liggen. Een reden kan zijn dat Crispijn een 'laag sociale' wijk is.

Appendix A5.2: Questions relevant for analyzing the hospital dataset

2.1 Heeft u cijfers over het aantal deelnemers vanaf maart 2017 tot eind 2018?

Cijfers over aantal deelnemers (ongeveer 300 tussen maart 2017 en juni 2018) zal ik je toesturen. Ook zal ik je laten weten wanneer de valpreventieprogramma's wanneer zijn geïmplementeerd.

2.2 Welke leeftijden doen over het algemeen mee en hoe is de verdeling qua mannen en vrouwen? Heeft u hier cijfers van?

De leeftijd van mensen die meedoen zijn vanaf 65. Dit is één van onze inclusiecriteria. Er komen geen ouderen die jonger zijn. Wel zijn er ook deelnemers die 80 jaar en ouder zijn, maar dat zie je zelden. De deelnemers zijn nooit ouder dan 85 jaar. Ik zal voor je kijken of ik ook de leeftijden en het geslacht van

de deelnemers aan je kan doorsturen (data was niet beschikbaar. Wel is er data opgestuurd over het aantal participanten en de kosten van de valpreventieprogramma's).

2.3 Waren er op dat moment (maart 2017) genoeg deelnemers om de programma's te vullen?

Ja, er waren zeker genoeg deelnemers. De deelnemers waren ook erg enthousiast om mee te doen. Het worden er dan ook elk jaar meer. Alle valpreventieprogramma's van 2019 zitten vol. Er is dus eigenlijk meer capaciteit nodig, maar er is niet genoeg geld beschikbaar.

2.4 In de vorige vergadering had u ook het logistieke probleem van ouderen aangestipt: dat zij niet (lichamelijk) in staat zijn om naar de valpreventieprogramma's te komen door de afstand die zij moeten afleggen. Klopt het dat de deelnemers die meedoen met de vitaliteits- en valpreventieprogramma's doorgaans uit de buurt komen van de fysiotherapiepraktijken?

- *Met andere woorden: is de kans groter dat je als oudere meedoet als je in Dubbeldam, Stadspolders, Crabbehof of Sterrenburg woont? Als voorbeeld: doen er veel ouderen van de andere kant van Dordrecht (over de N3) mee met de vitaliteits- en valpreventieprogramma's die u aanbiedt hier in Fysiotherapiepraktijk "Balanz"?*

Ja, dat klopt. Er is echt een enkeling die misschien komt van de wijken over de N3 (weg dwars door Dordrecht), de rest komt allemaal hier uit de wijk Stadspolders of Dubbeldam. Praktijk Schuilenburg heeft voornamelijk deelnemers uit Sterrenburg. Zo heeft elke deelnemende fysiotherapiepraktijk deelnemers die uit de buurt zelf komen.

Appendix A5.3: Questions about the costs of fall prevention programs

3.1 Een groot knelpunt voor het uitvoeren van deze programma's is dat valpreventie niet structureel wordt gefinancierd. Naast dat ik de effectiviteit van de valpreventieprogramma's aan het onderzoeken ben, ben ik ook een bepaalde financiële structuur aan het onderzoeken: de Health Impact Bond. Deze werkt op de volgende manier (laat concept van HIB zien). Ziet u kansen in een dergelijke financiële structuur? Zou u overwegen mee te doen met deze Health Impact Bond met uw fysiopraktijk?

Meneer Hendriks vindt dit erg lastig in te schatten. Als Fysiotherapeut zou hij het gevoel hebben zich steeds te moeten verantwoorden naar de investeerder of ondernemer, zeker als de ziekenhuiskosten (gerelateerd aan valincidenten) niet zullen dalen. Daarnaast verwacht hij dat door vergrijzing het aantal valincidenten zal toenemen de komende jaren. Het zou best kunnen zijn dat, ondanks dat er programma's zijn geïmplementeerd, de ziekenhuiskosten door valincidenten toch zullen toenemen. Dan lijkt het net alsof de programma's geen enkel effect hebben gehad op de ziekenhuiskosten, terwijl ze wel de groei van het aantal valincidenten hebben gestopt. Wanneer deze groeitrend zou worden meegenomen (door de onafhankelijke controleur) om de besparingen in ziekenhuiskosten te berekenen, dan zou het al aantrekkelijker zijn om als investeerder in een dergelijke Health Impact Bond te stappen.

Als meneer Hendriks (voor het geld wat hij zou krijgen van de ondernemer) alleen gebonden zou zijn aan een target om een vooraf bepaald aantal deelnemers voor de valpreventieprogramma's te behalen, dan zou meneer Hendriks geïnteresseerd zijn in een dergelijke constructie. Als de fysiotherapeuten dan ook nog een deel van de besparingen krijgen als 'bonus', dan zou deze incentive zeker bijdragen aan de aantrekkelijkheid van deze constructie voor de fysiopraktijken.

Hij heeft echter wel twijfels of het wel interessant is om als (private) investeerder in een dergelijke constructie te investeren. Hij verwacht dat de afspraken tussen de uitbetalende partijen en de investeerder moeizaam zullen verlopen en dat het erg complex zal zijn om met alle verschillende verzekeraars een deal te maken. Daarnaast is er op dit moment veel aandacht voor valpreventie in de (lokale) politiek en wordt er hard gewerkt om het aantal vallende ouderen terug te dringen. Een constructie als de Health Impact Bond zou hieraan bij kunnen dragen.

Conclusie: meneer Hendriks ziet veel barrières voor het succesvol opzetten van deze Health Impact Bond, maar ziet tegelijkertijd ook kansen om op deze manier met meer financiële middelen het aantal deelnemers te vergroten. Hij ziet het als een makkelijkere weg om ervoor te zorgen dat verzekeraars valpreventieprogramma's in het basispakket opnemen en dus volledig zullen vergoeden.

3.2 In mijn scriptie wil ik graag een voorbeeld geven van hoe een dergelijke structuur eruit zou zien. Ik wil daarin graag een inschatting maken van de kosten voor het opzetten en uitvoeren van de vitaliteitsprogramma's.

- *Wat zijn de kosten het opstarten van een vitaliteits- en valpreventieprogramma? Hoeveel ouderen doen er mee?*
- *Wat kost het geven van een vitaliteits- en valpreventieprogramma?*
 - Zaalhuur
 - Loon fysiotherapeut
 - Materiaal (cursusboeken, apparatuur om kwetsbaarheid te meten, etc.)
 - Lokale organisatie (busjes voor vervoer, etc.)
 - Reclame voor de programma's

Ik zal je alle begrotingen en kosten opsturen van de afgelopen jaren (data is opgestuurd en verwerkt).

3.3 Wat zijn de huidige kosten voor de ouderen die meedoen?

- *Hoeveel hiervan wordt er door de verzekeraar vergoed?*

De kosten voor het meedoen aan een valpreventieprogramma zijn 195 euro. Dit is het totale bedrag voor 10 lessen in 10 weken. Voor de vitaliteitsprogramma's betaalt een oudere 29 euro per maand. Het ligt aan de verzekeraar of deze kosten wel of niet worden vergoed. De meeste verzekeringen vergoeden de vitaliteitsprogramma's niet en sommige verzekeringen vergoeden de valpreventieprogramma's gedeeltelijk mits de ouderen een aanvullende verzekering hebben.

De meeste mensen zijn met VGZ verzekerd in Dordrecht. Bij een basisverzekering worden de programma's niet vergoed. Bij een aanvullende verzekering wordt er 50, 100 of 150 euro vergoed, afhankelijk van het pakket.

Het is jammer om te zien dat het vaak wel lukt om ouderen enthousiast te krijgen voor een programma, maar dat zij toch niet deelnemen om de kosten.

3.4 In 2014 en 2015, heeft u 50.000 euro gekregen van de gemeente om de mensen in Dordrecht te screenen op kwetsbaarheid en eenzaamheid. In 2017 heeft u 25.000 euro subsidie gekregen om de valpreventieprogramma's op te zetten en aan te kunnen bieden in 11 fysiopraktijken. In 2018 kreeg u 30.000 euro voor uitvoeren van de programma's in 14 praktijken en in 2019 zal u opnieuw 30.000 euro krijgen van de gemeente.

- *Heeft u voldoende subsidie ontvangen om alle kosten te dekken van het screenen van de ouderen en het opzetten van de valpreventieprogramma's?*

- *Is de jaarlijkse subsidie van 30.000 euro hoog genoeg om bewustwording te creëren van het valrisico van ouderen en het uitvoeren van de programma's?*

Voor het screenen is er twee keer 26.000 euro beschikbaar gesteld door de gemeente. Het kostte erg veel tijd en geld. De gemeente heeft dus een deel van deze kosten vergoed, maar zelf heb ik ook veel tijd in dit onderzoek gestoken zonder dat ik daarvoor iets heb gekregen. Dit kwam omdat er veel meer mensen zich hadden aangemeld dan vooraf was gedacht. Dit was mijn eigen keuze. Deze subsidie was dus eigenlijk niet voldoende, maar ik ben alsnog zeer tevreden dat het is gelukt.

De jaarlijkse subsidie die ik op dit moment krijg is voldoende om de programma's aan te bieden. Ze dekken het verschil tussen de inkomsten en de uitgaven. Er is echter weinig ruimte om reclame te maken voor het bestaan van de programma's. Het is niet alleen belangrijk om meer ouderen te kunnen bereiken, maar ook om ervoor te zorgen dat personen die werken in de zorg afweten van het bestaan van de programma's.

Indien het lukt om het doorverwijssysteem (beschreven in interview 1) te implementeren in het ASZ, dan is er extra geld nodig om een fysiotherapeut langs te laten komen bij ouderen met een verhoogd valrisico, die recent nog bij de valpoli of spoedeisende hulp van het ASZ zijn geweest. Het doorverwijssysteem en het langsgaan bij de ouderen thuis zal ervoor zorgen dat meer ouderen zullen meedoen met de valpreventieprogramma's.

Appendix A6: Main conclusions multidisciplinary meeting (2)

Verschillende stakeholders rondom het thema ‘Valpreventie’ zijn met elkaar samengekomen voor een tweede vergadering op 19 maart 2019 in Dordrecht. De volgende personen waren aanwezig bij de vergadering:

- Annemarie van der Velden (SEH-arts in het ASZ & medisch manager van de SEH)
- Fenna Verdenius (Voorzitter van het geriatrie netwerk Drechtsteden)
- Arno Hendriks (Fysiotherapeut en eigenaar van fysiopraktijk Balanz, medeoprichter van DrechtMax en bedenker van valpreventieprogramma’s)
- Marcel van Houten (Werkzaam als geriatrie fysiotherapeut bij fysiopraktijk Crabbehof, medeoprichter valpreventie programma’s & voorzitter van de ouderencommissie FysioDordt)
- Marieke Meinardi (Internist ouderengeneeskunde op het ASZ)
- Inge Logghe (Docent en onderzoeker op Hogeschool Avans)
- Martijn Michielse (Eigenaar van fysiopraktijk Fysique)
- Joost van Berckel (TU Delft student met als afstudeeronderwerp ‘Valpreventie’)

Het doel van de vergadering was om een samenwerkingsverband te creëren met betrekking tot valpreventie en op deze manier het probleem rondom vallende ouderen op een structurele en efficiënte wijze aan te pakken. Hieronder worden de belangrijkste punten in de vergadering samengevat.

Appendix A6.1: Introduction of the problem

De Spoed Eisende Hulp afdeling van het Albert Schweitzer Ziekenhuis (ASZ) heeft te maken met een toenemend aantal mensen die vallen (7 ouderen met letsel per dag). De meeste mensen worden na onderzoek en eerste hulp (85%) weer naar huis gestuurd, maar hebben vaak een hoog valrisico. De rest gaat naar het zorgtransferium of belandt in het ziekenhuis. In de huidige situatie komen mensen ook terecht bij de valpoli van de geriatrie afdeling en de geriaters sturen de ouderen met regelmaat door naar een geriatriefysiotherapeut. Het lijkt of de ouderen val steeds vaker recidiveren. Slechts een klein deel van deze kwetsbare ouderen neemt deel aan valpreventieprogramma’s.

In ‘De Drechtsteden’ zijn de volgende partijen actief bezig met valpreventie:

- Albert Schweitzer Ziekenhuis (ASZ)
- Dienst Gezondheid & Jeugd (GGD van Dordrecht)
- FysioDordt
- DrechtMax
- Geriatrie Netwerk Drechtsteden
- Huisartsen
- Thuisorganisaties
- Gemeentes

Appendix A6.2: Plan to create a multidisciplinary geriatric network

Er is afgesproken in de vorige meeting om een overzichtelijk multidisciplinaire structuur op te zetten. Dit betekent dat de volgende disciplines in het “Geriatrie netwerk Drechtsteden” gaan deelnemen:

- Geriaters (inclusief de valpoli)
- (Geriatrie)fysiotherapeuten
- Diëtisten

- Logopedisten
- Ergotherapeuten
- DrechtMax (alle aangesloten fysiotherapiepraktijken die het fitheid- en valpreventieprogramma DrechtMax aanbieden).

In een later stadium zal er worden onderzocht op welke wijze de huisartsen en neurologen (en wellicht andere afdelingen in het ziekenhuis) kunnen worden betrokken bij dit multidisciplinaire team. In de komende tijd zal er gewerkt worden om een totaaloverzicht te maken, zodat het duidelijk is welke rol alle belanghebbenden hebben.

Appendix A6.3: Plan to set up a system to give physiotherapist permission to contact elderly who have recently visited the hospital after a fall

Wat in toenemende mate voorkomt is dat een ouder persoon meerdere keren valt. Deze recidivisten hebben een hoog valrisico en zouden veel baat kunnen hebben bij het volgen van een valpreventieprogramma. Deze ouderen zouden kunnen worden doorverwezen naar de fysiotherapeuten door een doorverwijsysteem op te zetten. De basis van dit systeem is dat de patiënt een toestemmingsverklaring ondertekend waardoor het mogelijk wordt om actief contact te kunnen opnemen met die persoon. Het volgende is nodig voor een dergelijk systeem:

- Een verwijfsformulier voor de SEH met daarop naam en telefoonnummer van de betrokken patiënt.
- Een doorverwijsformulier voor de afdeling Geriatrie met naam en telefoonnummer van de betrokken patiënt.
- Een centraal meldpunt waaraan de gegevens van de ouderen kunnen worden gegeven die zijn gevallen of valgevaarlijk zijn (van de valpoli en de SEH).

Wanneer de patiënten zijn doorgegeven aan het centrale meldpunt van de fysiotherapeuten, dan zal er een geriatrie-fysiotherapeut bij de recentelijk gevallen of kwetsbare oudere langsgaan voor een screening. Afhankelijk van die screening worden er vervolgstappen bedacht.

Mevrouw Meinardi vroeg zich af of een dergelijk formulier nodig is, omdat er ook geen formulier nodig is om een casemanager in te schakelen voor ouderen die op de valpoli komen. Er wordt hier een ‘mondelinge’ overeenkomst gesloten.

Op de SEH ligt het weer anders. Zij zijn minder gebonden aan (privacy) regels, omdat het over spoedeisende hulp gaat. Het doorgeven van een medisch dossier kan echter niet zomaar worden overhandigd via dit doorgeefsysteem. Dus hier zal zeker toestemming voor moeten worden gevraagd. Het geven van slechts een nummer plus de naam zal echter geen probleem moeten zijn, alleen vraagt mevrouw van der Velden (SEH) zich af of zij haar collega’s wel zo ver krijgt om de gegevens van de patiënt te noteren en door te geven aan het centrale meldpunt. In de chaos van een SEH is het lastig om dit soort protocollen te implementeren.

Het medisch dossier van een patiënt zou via de huisarts kunnen worden opgevraagd, zodat (geriatrie)-fysiotherapeuten de juiste behandeling voor de betreffende oudere kunnen kiezen.

Appendix A6.4: The plan of the GGD to set up an overall approach to lower fall incidents

De Dienst Gezondheid en Jeugd (GGD) is bezig met een visie over een integrale aanpak van valpreventie. Er hebben al verschillende gesprekken plaatsgevonden tussen de GGD en Arno Hendriks. Binnenkort zal er een bijeenkomst komen waar alle partijen rondom valpreventie zullen worden uitgenodigd om te overleggen.

De focus ligt met name op het signaleren van ouderen met een verhoogd valrisico, voordat zij een valincident meemaken. Paramedici en andere personen die bij kwetsbare inwoners thuis komen

(wijkverpleegkundigen, verzorgenden, huishoudelijke hulp, etc.), moeten ouderen gaan informeren en motiveren, zodat zij deel gaan nemen aan een valpreventie- of vitaliteitsprogramma. Op deze manier is het mogelijk om ouderen voor een langere tijd zelfstandig thuis te laten wonen. Ook wordt er gekeken naar hoe ouderen verder kunnen worden ondersteund om mee te doen met de programma's. Zo kan er speciaal vervoer worden geregeld en is het belangrijk om het sociale netwerk van de ouderen te versterken.

Mevrouw van der Velden is van mening dat het ook belangrijk is dat er een paramedicus (bijvoorbeeld een ergotherapeut) kan meegaan met een oudere die net van de SEH afkomt. Het komt namelijk redelijk vaak voor dat er niemand is die de oudere komt ophalen. De paramedicus kan dan gelijk de thuissituatie van de oudere controleren om eventuele oorzaken van het vallen te constateren. Dit kan iets heel simpels zijn: bijvoorbeeld een los kleedje op de grond. Ook zou deze paramedicus de oudere kunnen adviseren om mee te doen aan een valpreventieprogramma.

Appendix A6.5: The relevance of the costs of fall prevention programs

Mevrouw Meinardi wijst erop dat er veel ouderen zijn die niet mee willen doen met de valprogramma's, omdat dit van hun fysio-budget af gaat. Of de ouderen moeten het zelfs helemaal zelf betalen. Wanneer de programma's zouden worden vergoed in de basisverzekering, dan zullen er naar verwachting een stuk meer ouderen meedoen met de programma's. Mevrouw van der Velden gaat dit bespreken met een projectmanager op het ASZ.

De resultaten van het onderzoek (van Joost van Berckel) naar de effectiviteit van de geïmplementeerde valpreventieprogramma's zouden geschikt kunnen zijn voor de gesprekken met zorgverzekeraars en kunnen helpen om de effecten van de programma's te evalueren op de lange termijn.

Appendix A7: Interview with Saskia Kloet at VeiligheidNL

Ik heb een interview gehouden op 8 mei 2019 met mevrouw Saskia Kloet. Zij heeft een rapport geschreven over valpreventie in 2016 en heeft veel kennis over de Health Impact Bond.

Het interview bestaat uit drie delen:

1. Vragen over de rol van VeiligheidNL bij het voorkomen van valincidenten in Nederland.
2. Vragen over de barrières voor het opzetten van een Health Impact Bond voor valpreventie.
3. Vragen over effectiviteit van valpreventieprogramma's en controleren resultaten van de case study.

Appendix A7.1: Vragen over de rol van VeiligheidNL in het voorkomen van valincidenten in Nederland

1.1 Het financieren van de programma's is een groot probleem. Landelijk is de participatie nog laag (1%) terwijl er wel aan alle kanten wordt bevestigd dat het een serieus probleem is. Financiering is een probleem en daarom kwam ik terecht bij uw rapport en de HIB. Lijkt me leuk om eerst meer te weten te komen over veiligheid NL. Wat doen jullie en welke rol hebben jullie met betrekking tot valpreventie? Welke projecten lopen nu allemaal en met wie werken jullie nauw samen?

Veiligheid NL is een stichting en wij werken in brede zin aan letselpreventie. Dus hoe kunnen we voorkomen dat er minder ongevallen of minder letsls door ongevallen gebeuren in Nederland. Dat doen wij vanuit een soort publieke taak en worden voor een deel gefinancierd vanuit een aantal landelijke overheden die in een aantal basisactiviteiten voor dit soort dingen financieren en deels aanvullend door onze regionale overheden en een aantal bedrijven.

Eigenlijk bestaat onze organisatie uit twee belangrijke takken, we hebben een onderzoeks-poot die ongevallen registreren. Onder andere dus in een steekproef van 14 spoedeisende hulpposten in Nederland.

Wij hebben hier de module 'letsls en de leefstijlmonitor'. Waarmee we dus ook uitspraken kunnen doen over letsls die niet op de spoedeisende hulp terecht zijn gekomen maar wellicht wel een medische behandeling hebben gehad of onbehandeld zijn gebleven. We hebben toegang tot de data van de ziekenhuisopname en zo kunnen we eigenlijk vanuit dat programma een goede weergave maken van de letselproblematiek in Nederland.

We doen dit al 35 jaar dus we hebben daar echt een hele steady basis aan gegevens over de letselproblematiek in Nederland. Daarnaast hebben we nog verschillende modellen die we onderhouden en aanpassen: dat valt eigenlijk ook in die onderzoektak. Met deze modellen kunnen we bijvoorbeeld zeggen: deze persoon heeft dit type letsel, daar worden gemiddeld zoveel medische kosten voor gemaakt en is er meestal zoveel arbeidsverzuim wat gelijkstaat aan zoveel kosten.

Dus we kunnen ook berekenen hoeveel een bepaald letsel kost en kunnen we uiteindelijk ook kosten-baten analyses maken voor preventieactiviteiten. Dat is een beetje die tak van Veiligheid NL.

Ook financieren we een aantal preventieprogramma's bij Veiligheid NL, die worden ook meegefinancierd door VWS of andere partijen, fondsen en bedrijven. Dat verschilt heel erg.

In die preventieprogramma's proberen we activiteiten uit te voeren die bijdragen aan het verminderen van die ongevallen of het verminderen van de ernst van die ongevallen. Dat is onze missie. Dat doen we op een aantal hoofdonderwerpen. De eerste is: veilig opgroeien voor jonge kinderen (1). Dan heb je het over onderwerpen als veilig slapen, dus voorkomen van wiegendoed; komt niet vaak voor maar het overlijden meteen is natuurlijk wel superheftig. Verbranding, vergiftiging, vallen van de commode, de trap of de fiets. Verstikking, onderdeeltjes van speelgoed in de mond, ogen, neus, oren.

Het tweede hoofdonderwerp is ‘Vitaal ouder worden’ (2) waarbij het belangrijkste onderwerp valpreventie is, want ongeveer 80% van de ongevallen zijn val-gerelateerd bij ouderen. Het derde hoofdonderwerp is sportblessurepreventie en veilig werken (3).

1.2 Laten we focussen op onderwerp 2: valpreventie in de ouderenzorg. Ik heb gelezen dat jullie van het Ministerie van Volksgezondheid Welzijn en Sport opdracht hebben gekregen om te onderzoeken of een Health impact Bond een goed financieringsinstrument is in de ouderenzorg. Doen jullie dit met name voor het ministerie of voor jullie eigen activiteiten?

Eigenlijk willen wij het weten. Onze missie is het voorkomen van ongevallen. Bij ouderen zijn het vooral valongevallen. Het is een probleem wat steeds erger wordt. Deels heeft dat te maken met het aantal ouderen dat toeneemt en deels komt dat doordat het risico op een val toeneemt. Tegelijkertijd is er veel bekend over effectieve valpreventie. En zijn er meerdere programma’s en screenings-interventies in Nederland op de markt die ingezet kunnen worden. Wat we zien is dat er in de praktijk veel te weinig gebruik wordt gemaakt van die effectieve interventies. Of organisaties bedenken zelf iets. Van ‘ja we gaan dan posters ophangen door de hele gemeente en daarmee doen we aan valpreventie’, dat is niet effectief. Dus er is heel veel bekend, maar het wordt niet voldoende en effectief toegepast. Dat zit voornamelijk in twee dingen:

- 1) De motivatie van ouderen om überhaupt deel te nemen aan dit soort programma’s. Er hangt een soort stigma van ouder worden en kwetsbaarheid en dergelijke op. Het is ook een kwestie van frames van dit soort programma’s. Wij noemen ze al bewust geen ‘valpreventieprogramma’s’ meer. Zoals in zo’n interview wel, maar naar buiten toe worden ze geprofileerd als ‘In balans’ of ‘Langer Thuis Wonen’. En dat is ook wat je doet. Want we verbeteren mobiliteit en we verbeteren spierkracht en balans, maar wel ten dienste van valpreventie. Maar dat hoeven zij dan niet zo precies te weten. Dus er worden verschillende bewegingen gemaakt om ervoor te zorgen dat er niet zo’n hoge drempel meer is voor dit soort programma’s.
- 2) Het andere element waardoor het vaak spaak loopt is het feit dat er veel organisaties betrokken zijn bij valpreventie: er is niet 1 partij, er is niet 1 professional, er is niet 1 organisatie die alles doet. Er moeten altijd meerdere partijen bij betrokken zijn en dat maakt zowel de organisatie als de financiering ervan lastig. Want wie betaalt dan wat en waar komen de besparingen terecht?

In de praktijk denk ik dat de gemeentes nog steeds de grootste financier zijn van valpreventie-activiteiten, terwijl daar het kleinste aandeel van de besparingen terecht komt. Er is dus een soort onbalans. Wij praten al 10/20 jaar met zorgverzekeraars en daar is het ook allemaal moeilijk en ingewikkeld, want die zitten met een risico en die weten niet of ze wel kunnen voor-investeren. Daarom zou een alternatieve vorm van financieren, zoals een HIB, een goede mogelijkheid zijn om dat te kunnen doorbreken.

1.3 Om het algemene deel Veiligheid NL af te sluiten: jullie focussen op heel Nederland, jullie doen dus onderzoek en jullie doen actief mee met het ontwikkelen en financieren van valpreventieprogramma’s. Klopt dit?

In principe helpen we in het ontwikkelen van programma’s, zodat ze door lokale partijen geadopteerd en geïmplementeerd kunnen worden. Soms is het nodig om aan maatschappelijke agendering te doen en wordt het een PR-campagne om überhaupt aandacht te vragen voor dit onderwerp. Dus het hangt af van het thema en het doel en de fase. Zoals voor gehoorschade is er nog heel veel agendering nodig om tussen de oren te krijgen dat we hier echt wel te maken hebben met een serieus probleem. Dus we focussen daar nu veel op agendering, terwijl voor valpreventie we weten dat we vooral dicht bij de professionals moeten zitten om iets gedaan te krijgen.

1.4 Er is dus niet één bepaalde partij die alles regelt, maar vele lokale partijen die overal samen moeten werken. Zou het een oplossing zijn om een grote organisatie te maken daarvoor?

Je blijft altijd afhankelijk van de lokale spelers. Dus ik vraag me af of het zal werken. Tenzij er een rijke familie is die 10 miljoen per jaar wil investeren om dit programma door heel Nederland uit te rollen, maar die zijn er niet.

Effectieve valpreventie hangt af van drie elementen. 1) Je moet de juiste ouderen weten op te sporen (*patient-finding*) en die vervolgens screenen op een valrisico. Dit kan een praktijkondersteuner doen door bijvoorbeeld in patiëntendossiers te kijken of ze in de 6 maanden daaraan voorafgaand gevallen zijn. Of ze meer dan 3 typen medicatie gebruiken of valrisico-verhogende medicatie gebruiken. Of ze hart- en vaatziekten hebben, of ze bloeddrukverlagers slikken. Een mantelzorger zou met twee vragen te weten kunnen komen of iemand een verhoogd valrisico heeft. Een thuiszorgmedewerker zou het ook kunnen doen. Er zijn alleen al voor die stap verschillende mensen die daar iets in zouden kunnen doen. (2) Tweede stap is dat er een effectief Multi-factoreel programma volgt. Waarbij in het programma aandacht is voor bewegen, medicatie-gebruik en visus, dus goede bril, woningaanpassingen en voeding (vitamine D en eiwitten zijn belangrijk). Uit de literatuur is bekend dat door aan al die factoren iets te doen je het hoogste effect bereikt. Er is ook bewijs voor alleen beweegprogramma's en alleen medicatie aanpassing maar nog beter is die multifactoriële aanpak.

En de laatste stap (3) is de goede uitvoering ervan in de praktijk. Want dat zie je vaak niet gebeuren. Wij adviseren vaak het programma 'In Balans', een 14-weeks beweegprogramma. Dit is super effectief: 60% val-reductie. En dan gaan mensen daar in de lokale praktijk mee aan de slag. Het programma is 14 weken, waarvan 11 weken 2 keer per week bewegen. En dan zeggen ze 'ja maar 2 x per week bewegen krijgen we niet voor elkaar, dus we doen het 1 x in de week'. Dat kan. Vind ik niet heel erg, maar dan boet je in aan effectiviteit. Dus dan kijken wij wat is ervoor nodig om te zorgen dat het wel twee keer in de week gebeurt. Of moeten we accepteren dat het niet zo is en het programma aanpassen, maar dan ook minder effect en wel een grotere afzet. Dat kan. Dat zijn vraagstukken waar we mee bezig zijn.

Deze drie elementen maken een valpreventie-aanpak effectief. En voor al die elementen heb je verschillende lokale professionals nodig om dat uit te voeren. Kan je bijna niet vanuit het landelijke organiseren. Je wilt aansluiten bij, bijvoorbeeld in sommige gemeente kan een kerkgenootschap een hele goede ambassadeur zijn voor ouderenpopulatie, terwijl dat in een andere gemeente een bridgeclub of ouderenbond is. Daar wil je bij aansluiten juist ook om die ouderen daar te krijgen. Dus dat maakt het wel lastig. Ik denk niet dat een soort van landelijke valpreventie B.V. oprichten de oplossing gaat zijn. De focus moet lokaal zijn. Voor ons als organisatie zit het 'm echt in hoe krijgen we die lokale organisatie beter. Wat moet daarvoor gebeuren en hoe krijg je die financiering beter.

1.5 In Dordrecht zijn ze nu ook heel erg bezig met dat als ze al zijn gevallen, om een soort doorgeefsysteem te maken vanaf de SEH naar de fysio. Zij willen een soort formulier maken waarop de patiënt toestemming geeft dat er een persoon langskomt. FocusSEN jullie daar ook op?

Dat zou ideaal zijn. Dat soort goede voorbeelden proberen wij vaak op te halen en ook te delen. De VU Amsterdam wil het ook heel graag. Een soort ketenaanpak: mensen komen op de SEH met een val. Je weet dat zij een verhoogd valrisico hebben als je eenmaal gevallen bent. Hoe kun je de follow-up daarvan goed organiseren? Wie verwijst door? Want als je alleen die ouderen een briefje geeft van je moet naar de huisarts, dat gaat in 90% van de gevallen niet gebeuren.

Maar wie gaat dat dan betalen? Voor dit soort preventie-activiteiten is niet een standaard betaalsysteem in ons zorgsysteem. Dat maakt het lastig. In sommige gevallen betaalt de gemeente huisbezoeken en in sommige gevallen maken zorgverzekeraars en gemeente afspraken daarover. Dat praktijken een screening doen onder een andere DBC-code bijvoorbeeld. Die afspraken worden niet landelijk gemaakt.

Appendix A7.2: Vragen over een Health Impact Bond

2.1 Is er al een (succesvolle) HIB ergens opgezet in Nederland? Ik heb gelezen over het ‘Sociaal hospitaal’, waarin een HIB helpt in het oplossen van problematiek van probleem gezinnen in den Haag. Bent u daarbij betrokken?

Het sociaal hospitaal is meer een Social Impact Bond en daar zijn we niet bij betrokken. Wereldwijd zijn er een aantal HIBs. In Engeland voor astma en in Amerika is er dacht ik ook één. Voor zover ik weet zijn er geen valpreventie HIBs.

We zijn overigens in Noord-Limburg bezig om te kijken of we het daar voor elkaar kunnen krijgen omdat daar de gemeente en de zorgverzekeraar en zorgkantoor de handen ineen hebben geslagen om het serieus te verkennen.

De zorgverzekeraar mag echter geen winst uitkeren. Als er echter echt bereidheid is van mensen en organisaties om dit uit te proberen dan gaan ze (VWS) daar experimenteerruimte voor regelen.

2.2 Als dat gebeurt, zal er dan een wetswijziging komen?

Dat zou nog geen wetswijziging zijn maar dan zouden ze dus zeggen: ‘ten behoeve van dit experiment willen we toestaan dat deze partij in deze situatie onder deze omstandigheden besparing op zorggeld uitkeert aan partijen buiten de zorg.’

2.3 Waarom komt valpreventie niet in de basisverzekering?

Idealiter wil je valpreventie in het zorgstelsel, in de basisverzekering. Als ik het voor het zeggen zou hebben.

Wij zijn erover in gesprek met VWS, ook met zorgverzekeraars. En dan worden we toch teruggefloten door alle individuele verzekeraars: ‘dit is concurrentieel terrein voor ons dus daar gaan we geen collectieve afspraken over maken, want ik maak daar wel of niet winst op, op het verkopen van dit soort polissen’.

Nu komt er wel landelijk steeds meer het besef dat er misschien wel iets moet gebeuren. De G.L.I. (Gecombineerde Leefstijl Interventie) was een eerste experiment om op grootschalige manier preventie in het zorgstelsel te krijgen. Afgelopen jaar is dat helemaal rond gekomen, vanaf 1 januari 2019.

Er kunnen preventie-activiteiten rondom overgewicht preventie worden vergoed vanuit de basisverzekering met allerlei voorwaarden. Ik vermoed dat dat ook moet kunnen voor valpreventie. Tenminste, daar hebben wij gesprekken over met verschillende ministeries. Dat gaat over een aantal directies binnen VWS om te verkennen of valpreventie zich hier ook voor leent. Maar wat daar nu voor nodig is, is dat je heel goed in kaart moet brengen, wat de doelmatigheid is van de verschillende stappen. Dus stel, je wil een valrisico-screening in het basispakket: geldt dat dan voor iedereen? Vanaf welke leeftijd? Vanaf welke leeftijd is het doelmatig om zo'n screening te doen? Want stel je doet het vanaf 50+, dan ga je heel veel mensen vinden die geen verhoogd valrisico hebben en ga je dus veel geld besteden om een relatief kleine populatie te vinden. Dus je kunt ook zeggen vanaf 75+, want we weten ongeveer uit de literatuur dat 80% daar een verhoogd valrisico heeft. En hoe effectief is de follow-up van zo'n screening? Stel je verwijst iemand door, hoe groot is de kans dat iemand ook daadwerkelijk gaat deelnemen aan dat programma? Dus daar moeten nog dingen in uitgezocht worden voordat het in de verzekerde zorg kan komen. Plus dan moet je gaan uitzoeken welke professionals dit kunnen uitvoeren en welke competenties moeten zij dan minimaal hebben? Want dan ga je vaststellen dat bijvoorbeeld zo'n valrisico-screening gedaan mag worden door: een ergo, een fysio, een praktijkondersteuner. Dan kun je betaaltitels gaan maken. Maar dat is een proces wat ik denk dat wel gaat gebeuren. De G.L.I. heeft negen jaar geduurd. Ik denk echter dat het met valpreventie sneller kan,

omdat ze heel veel geleerd hebben van de G.L.I. Maar als het van 9 naar 6 jaar kan dan is iedereen volgens mij al heel blij. Dat soort dingen lopen gewoon heel langzaam, maar ik denk dat er op een gegeven moment toch bepaalde elementen van zo'n valpreventie-aanpak vergoed zullen worden vanuit de basisverzekering.

2.4 Ethisch puntje. Als ouderen niet meer vallen, dan leven ze langer en dat brengt veel kosten met zich mee. Het zou kunnen zijn dat zorgverzekeraars op lange termijn niet goedkoper uit zijn. Wat is de mening van de zorgverzekeraars hierover?

Dat is de preventie-paradox. Ze leven inderdaad dan langer en de meeste zorgkosten worden gemaakt in het eerste en laatste levensjaar, gemiddeld genomen. Maar met dit argument zou je alle preventie zullen killen. Dit argument speelt zeker onder zorgverzekeraars. Om het voor elkaar te krijgen moet je voor de zorgverzekeraars alle hobbels wegnemen: zo gaan we het meten, hier bespaar je geld etc.

2.5 Dus er is veel weerstand van zorgverzekeraars?

Ons huidige zorgstelsel is op dit moment ook niet houdbaar, dus er moet wel iets gebeuren. Er is een sterke focus op zorg in plaats van gezondheid. Daarnaast is er op dit moment een focus op betalen per verrichting in plaats van betalen per resultaat. Ik denk dat het bijna onoverkomelijk is dat dit zal veranderen. Dus ook zorgverzekeraars zullen hier uiteindelijk in mee gaan.

Die hoogste kosten in het laatste levensjaar gaan we ook met valpreventie-activiteiten niet voorkomen, maar je gaat wel in de tijd tot dat laatste levensjaar de kwaliteit van leven verbeteren en de zorgvraag verminderen, want lang niet iedereen overlijdt door een val. Er komen er 102.000 op de SEH en slechts 4000 overlijden. Heel veel mensen hebben daarna zorg nodig door die val, dan heb je toch liever dat je dat ook tussendoor al zorgkosten voorkomt en kwaliteit van leven verbetert? Het kan in mijn ogen dus ook twee kanten op werken.

Er is nog een ander probleem. Stel, nu in Dordrecht hebben ze die valpreventie aanpak in een deel van de stad uitgevoerd. Daardoor komen minder mensen waarschijnlijk op de SEH, daar zit ook een gek ding in de zorg. Want de SEH gaat uiteindelijk niet minder mensen opnemen, maar ze krijgen ruimte om andere mensen op te nemen die ze anders misschien niet zouden opnemen of door zouden sturen naar de HAP. Omdat er nou eenmaal afspraken met de zorgverzekeraars zijn gemaakt. Een ziekenhuis gaat niet onder dat plafond zitten, want dan snijden ze in hun eigen portemonnee. Waardoor de zorgverzekeraar zegt 'ja we geloven wel in valpreventie en dat je daarmee heupfracturen/polsfracturen/SEH bezoeken kan voorkomen, maar die besparing is voor ons niet direct een *out of pocket* besparing omdat het ziekenhuis toch wel hun omzet gaat maken'.

Je zou ook kunnen beredeneren, dat je (als zorgverlener) een aantal jaar gaat bijhouden hoeveel mensen binnenkomen op de SEH in de tijd van de HIB. Als je dat ziet afnemen dan betekent dat, dat je een onderhandeling aangaat met je zorgverlener als zorgverzekeraar: je kan dus scherper onderhandelen.

2.6 Een groot knelpunt voor het uitvoeren van deze programma's is dat valpreventie niet structureel wordt gefinancierd. Naast dat ik de effectiviteit van de valpreventieprogramma's aan het onderzoeken ben, ben ik ook een bepaalde financiële structuur aan het onderzoeken: de Health Impact Bond. Ik denk dat het handig is om de HIB aan de hand van een plaatje te bespreken (figuur van hoofdstuk 7).

Veel andere belangen spelen mee voor verzekeraars en de overheid. Maar stel: ze zouden wel bereid zijn om mee te doen. Ze moeten dan een contract sluiten. In hoeverre denk je dat dat haalbaar is? Mijn onderzoek heeft aangetoond je veel gezondheidszorgkosten kan besparen. De vraag is: waarom lukt een dergelijke structuur nou niet? Eén van die punten is dus dat verzekeraars geen winst mogen uitkeren. Zijn er nog andere zaken die meespelen?

Er spelen wel meer zaken, maar die concentreren zich allemaal wel het meest op het uitbetalingsconcept. Wij hadden gehoopt hier al een experiment te kunnen doen, maar zover kwam het niet. Nu hopen we dat wel in Noord-Limburg te doen, zodat we iets meer weten over de praktische haalbaarheid ervan.

De vraag is: hoeveel risico is een investeerder bereid om te nemen? Want dat bepaalt mede de afspraken op basis waarvan je gaat uitbetalen. Hoe strikt of hoe ruim die zijn. Dat bepaalt dus ook mede wat er allemaal geregistreerd moet worden. Hoe je zo'n valpreventieprogramma opzet, hoe je dat lokaal kan organiseren, wie je daarvoor nodig hebt. Wat het oplevert. Die kosten-batenanalyse hebben we daar al wel. Dus daar weten we al heel veel over. Dit kan allemaal. Als er een hele strenge winter is, er ligt veel ijs, dan gaan veel mensen vallen. Hoe ga je dat soort ontwikkelingen corrigeren? Een landelijk beleid? Kan je vooraf het effect niet van overzien. Nu heb je de beleidswijziging dat mensen langer thuis moeten blijven wonen, leidt natuurlijk tot meer val-ongevallen maar over 3 tot 4 jaar kun je daar iets over zeggen. Dat kun je niet op basis van 6 maanden concluderen. Dat is heel lastig om dat aan te tonen. Dit is een grote uitdaging.

Ook het uitbetalen is een grote uitdaging. Zorgverzekeraars en zorgkantoren zijn wettelijk beperkt in wat ze mogen uitbetalen buiten de zorg. Of daar komt experimenterruimte vanuit VWS of een zorgverzekeraar haalt dat bijvoorbeeld uit zijn eigen middelen als voor-investering. Een zorgverzekeraar heeft ook heel veel marketingbudget of innovatiebudget. Je zou kunnen overwegen om het eerst daaruit te betalen. Wat ook speelt: om te meten of het effect heeft, jij hebt nu analyse gedaan op de dataset van het ziekenhuis. Onderscheid gemaakt in de verschillende wijken en leeftijdsgroepen. Dus dat je op een ziekenhuis-niveau kan meten hoeveel mensen er binnenkomen ten gevolge van een val en wat de gevolgen waren. Dat zit check, dat gaat lukken. Ook qua privacy. Dit systeem kan worden uitgerold in ieder ziekenhuis. Jouw onderzoek kan daar zeker in bijdragen.

2.7 Stel, we gaan een HIB in een gemeente opzetten, er is een investeerder. Kunnen ze jullie dan bellen voor de benodigde data?

Dan gaan wij naar het lokale ziekenhuis. Nu in Noord-Limburg zijn we in gesprek met het lokale ziekenhuis. We vragen: wat monitoren/registreren jullie al van mensen die op de SEH komen bespreken we dan met het lokale ziekenhuis. Kun je daar een aantal andere indicatoren bij registreren voor deze HIB? Of wil je bijvoorbeeld bij ons L.I.S. (letsel Informatie Systeem) aansluiten, zodat je het ook gelijktrekt met wat er landelijk geregistreerd wordt.

2.8 Als je valt in Dordrecht dan ga je sowieso naar Albert Schweitzer. Is het in een andere stad moeilijker om te monitoren waar de ouderen vandaan komen die zijn gevallen?

In Dordrecht kan het. In Amsterdam Zuid hebben we ook gekeken hoe haalbaar het is om val ongevallen te monitoren. Dit is heel moeilijk, want sommige gaan naar de Amstelveen, OLVG, Spaarne ziekenhuis VU, AMC, Amstelland of zelfs Hoofddorp. Je zou in plaats van monitoren via ziekenhuis ook via bevolkingsmonitor kunnen monitoren hoe vaak mensen gevallen zijn en daardoor op de SEH beland zijn.

2.9 Hoeveel risico is een investeerder in jouw ogen bereid te nemen? Zouden zij instemmen met de methode die ik gebruik heb? Waar in dit overzicht van HIB zit het grootste risico voor de investeerder?

Het is met publieke preventie heel erg lastig om in een gemeente, waar je een aanpak gaat uitrollen, een soort controlesgroep in te richten. Ga je dat bij een andere gemeente organiseren met dezelfde populatie-samenstelling? Of je zou kunnen kijken, o.b.v. de bevolkingsopbouw in Dordrecht zou het zo moeten gaan stijgen. Wij hebben heel veel gegevens van andere regio's, dus daar zou je het tegen af

kunnen zetten. Er zijn dus alternatieven voor een RCT, maar daardoor is het monitoren onzekerder en creëer je marge en buffer die je bij een RCT niet hebt.

Daar zit die risico -bereidheid van de investeerder: het ligt er dus aan hoe strikt de afspraken over uitbetaling zullen zijn. Als zij (de uitbetalers) zeggen: het moet oorzakelijk bewezen zijn dat de aanpak heeft geleid tot minder heupfracturen, dan wordt het best spannend, want dan moet je eigenlijk een grote controle- en interventiegroep hebben. Als zij zeggen: als we zien op populatieniveau dat de kwaliteit van leven is verbeterd dan vinden we dat voldoende en heb je maatschappelijk impact bereikt; want we weten dat het lijdt tot minder zorgkosten. Dan hoef je niet het directe oorzaak-gevolg te bewijzen. Daar zit een stukje risico-bereidheid van die investeerder in. Voor mijn gevoel zit het 'm dus (dat risico) vooral in dit deel, omdat over de rest van een Health Impact Bond genoeg bekend over is: we weten dat als er geld is, dat we dit wel voor elkaar krijgen.

2.10 Denk je dat het effectiever is als valpreventie in de basisverzekering komt?

Ik denk dat de basisverzekering veel effectiever is, hoewel ik toejuich dat dit soort experimenten gebeuren. Ik hoop echt dat we dit voor elkaar krijgen juist om te laten zien dat je ook resultaatgericht zorg kan financieren en niet alleen maar behandelgericht. Daar alleen al kan het experiment interessant voor zijn.

2.11 Waarom investeert het ministerie van VWS niet zelf om een HIB-pilot project op te zetten?

Als het blijkt dat een HIB werkt, dan zal de interesse van investeerders toenemen en zouden er wellicht verschillende HIB-constructies kunnen worden gevormd in verschillende delen van het land.

Als de overheid investeert dan is het niet een HIB, want een deel van het geld gaat terug naar de overheid, dus de overheid is zelf belanghebbende. Het principe is dan helemaal anders.

De overheid, met de toenemende zorgvraag, heeft nooit genoeg geld om aan die toenemende zorgvraag te gaan voldoen. Zij willen juist met dit soort experimenten een deel daarvan ondervangen. Dan is zowel de investeerder als de overheid geholpen.

Ik denk zelf, dat als een HIB voor valpreventie niet lukt, dat het dan voor geen enkel ander gezondheidsonderwerp lukken. Over dit onderwerp is veel bekend en er zijn kosteneffectieve programma's ontwikkeld. Je kan het op korte termijn meten. Je hoeft niet zoals bij rookpreventie een HIB voor 20 jaar te gaan doen. Valpreventie is relatief kort na de cursus al te meten: een In-Balans-cursus verlaagt het valrisico volgens een RCT met 60 %, dus dat moet je binnen een jaar al terug kunnen zien bij een huisartsenpraktijk of SEH en meetbaar kunnen maken. Er zijn zoveel ingrediënten waarom dit onderwerp zich ervoor leent, waardoor ik denk dat dit concept breder in gezondheidszorg niet van de grond zal komen als het bij valpreventie niet lukt.

2.12 Je zegt: dit gaat sowieso goed. Stel je had een miljoen, had je het dan geïnvesteerd in een HIB?

Ja, dat had ik zeker gedaan. We hadden tijdens ons onderzoek zeker zes investeerders klaar staan die wilden investeren in een HIB, maar er is geen uitbetalen. Voornamelijk de zorgverzekeraar zit dwars, zoals ik eerder heb besproken.

Het ligt dus niet aan de investeerder. De investeerders zijn er genoeg, zowel banken als rijke families hebben geld over voor een maatschappelijk doel waar ze ook een grote kans hebben om het geld met een marge terug te krijgen. Daar hadden we er meerdere van. Maar het gaat erom dat er iemand bereid moet zijn uit te betalen aan de investeerder.

2.13 En als je het alleen doet vanuit de WMO en de WLZ? Dus zonder de zorgverzekeraar.

WMO heeft een te klein aandeel in de besparingen. Met alleen de WMO zou het niet rendabel zijn. Met de WLZ zit je weer dichtbij de overheid en die werken niet mee als de zorgverzekeraar dat niet doet. We hebben nog gekeken in Utrecht. Daar was een thuiszorgorganisatie, die belang had bij preventie, omdat zij een 3-jarig contract hadden afgesloten met de zorgverzekeraar. Preventie zou gunstig zijn, want dan kunnen ze hun patiënten langer en met dezelfde persoon bedienen. Dit levert structuur en inkomsten op. Waar ze zichzelf mee in de vinger hadden gesneden, is dat ze het budget niet jaarlijks hadden verhoogd en wel zagen dat de vraag toenam. Dus zij hadden ook belang bij preventie om hun kosten te drukken. Helaas was hier het aandeel thuiszorg niet voldoende om een rendabele businesscase te maken. Je hebt echt de zorgverzekeraar nodig om een HIB voor elkaar te krijgen. Het aandeel van de gemeente is ongeveer 10% (de WMO). ZVW 55% en de WLZ 35%.

Appendix A7.3: Vragen over effectiviteit van valpreventieprogramma's

3.1 Zou je even willen meekijken naar mijn resultaten? De kostenbesparingen zijn rond de 3 ton. Zijn dit reële getallen?

Ik denk dat dit zeker reële getallen zijn, die ongeveer met onze eigen rekenmethode zouden overeenkomen. Onze rekenmethode op onze website maakt een grove schatting van de verwachte kostenbesparingen. Deze gaat uit van een 5-jaars aanpak. Je vult in hoeveel mensen in de 65+ categorie in de target groep wonen. Een deel daarvan heeft een verhoogd valrisico en een deel daarvan zou ook echt kunnen deelnemen in de valpreventieprogramma's.

Je kan je eigen resultaten even daartegen spiegelen en kijken of het ongeveer overeen komt. Even denken hoe ik je met die kosten kan helpen. Het model mag ik niet vrijgeven. Het enige wat ik zou kunnen vragen, dat wat je erover opgeschreven hebt kan ik bij mijn collega laten toetsen. Wat hij ervan vindt. Of het een beetje in de richting of in lijn is met jouw uitkomsten.

3.2 Hoe is de analyse gedaan in het rekenvoorbeeld van je rapport over valpreventie?

In het rapport hebben we eenzelfde (eenvoudige) analyse gedaan, die van het positieve is uitgegaan. Deze analyse, in dit rekenvoorbeeld en ook in de rekenhulp (op de website), gaat ervan uit dat je de juiste subgroep naar de juiste interventie lijdt en dat die interventie ook echt uitgevoerd wordt zoals bedoeld. Dus als je het programma In-Balans uitvoert dat je ook echt 14 weken 2 x per week minimaal een uur zal bewegen onder begeleiding van een fysiotherapeut. Dat zijn aannames die zijn vastgezet. We weten dus dat het in de praktijk lang niet altijd zo gebeurt en daarom is het rekenvoorbeeld uitgegaan van een vrij positieve situatie.

Er is nog iets anders waar je rekening mee moet houden. Omdat heupfracturen minder vaak voorkomen moet je populatie groter zijn. Afgelopen jaar in verschillende regio's hebben we een nieuw programma getest: Thuis Onder Mobiell. Kosten en baten in kaart gebracht. Als er in 1 jaar tijd 30 a 40 ouderen deelnemen en er heeft maar 1 iemand toch een heupfractuur dan ben je al bijna niet meer kosteneffectief. Omdat de kosten op zo'n kleine populatie niet zo groot zijn. Er is wel een minimale massa nodig om zeker te weten dat je een x aantal heupfracturen en/of andere dure letsel gaan voorkomen. Hoe kleiner je massa hoe groter de kans op 1 heupfractuur die toch nog weleens kan gebeuren. Het risico op vallen wordt groter, maar je hoopt dat het risico op letsel minder wordt.

3.3 Als er inderdaad zoveel te halen valt door valpreventieprogramma's op te zetten, hoe kan het dan dat er nog zo'n klein deel van de ouderen meedoet aan deze programma's?

Wat ik me altijd afvraag: waarom moet het in de preventie zo moeilijk? Het zijn maar marginale kosten om het mogelijk te maken. De kosten om dit voor duizenden mensen mogelijk te maken staan gelijk aan de kosten om 1 kankerpatiënt immunotherapie te geven. Terwijl je die kankerpatiënt niet gaat genezen en je met valpreventie weet dat je vallen kan voorkomen. Dat zijn ethische vraagstukken; heel erg ingewikkeld. Ook frustrerend.

Appendix B: Data preparation and cleaning

The data from the multiple sources had to be cleaned and prepared in order to use the DID method to determine the effectiveness of the fall prevention programs. In the table below, the main cleaning and preparation activities are listed. The python code to clean and prepare the data can be found in appendix G.

Table 11: Data preparation and cleaning

Activity	Dataset	Related to outcome measure
Load dataset and delete irrelevant columns.	Hospital data ASZ	All
Load dataset and delete irrelevant columns.	Cost- and classification DOTs	All
Keep only the data with diagnosis related to fall incidents.	Hospital data ASZ and cost- and classification DOTs (now merged into one)	All
Remove duplicate DOTs registered on the same day.	Hospital data ASZ	All
Drop the DOTs created in 2013.	Hospital data ASZ	All
Drop the registration where a patient died in 1925.	Hospital data ASZ	All
Drop the DOTs of older adults living in a nursing home.	Hospital data ASZ	All
Replace the missing DOT codes with a DOT code with the lowest costs and severity (E.G. 'Ambulant light'-DOT).	Hospital data ASZ	All
Load dataset and delete irrelevant columns.	Dutch Zip Code dataset	All
Drop the rows with wrong zip-codes and therefore missing values (as the ASZ dataset has been merged with the Dutch Zip Code dataset).	Hospital data ASZ and Dutch Zip Code dataset (now merged into one)	All
Create a new column with age groups 65-75, 75-85 and 85+.	Hospital data ASZ	All
Create a new column with the analysis year (from sept year x to sept year y). This is because the programs were implemented in March 2017 and it takes time before the programs have an effect on the hospital expenditures.	Hospital data ASZ	All
Create a new DataFrame where the row with the most severe fracture is saved and the rest of the fractures (on the same day with the same patient-number) are deleted.	Hospital data ASZ	Number /severity of fall incidents
Load datasets and delete irrelevant columns.	Population per age group datasets ('14,'15,'16,'17,'18)	All
Create a new column with age groups 65-75, 75-85 and 85+.	Population per age group datasets ('14,'15,'16,'17,'18)	All
Combine population datasets.	Dataset population combined	All
Convert format and shape of DataFrame to the format of the ASZ dataset.	Dataset population combined	All
Filter data on relevant zip codes. Zip codes covering large areas such as Industrial or agricultural areas are not included.	Dataset population combined	All
Filter data on relevant zip codes.	Hospital data ASZ	All
Delete data in 2014 up until September 2014 (as the analysis years are from Sept year x to Sept year y).	Hospital data ASZ and dataset population combined	All
Delete unreliable data in 2018 (October, November, December). This is because the data has been requested in January 2019. Many DOTs from this period were not closed.	Hospital data ASZ and dataset population combined	All

Create a new column with 'no group', 'intervention group' or 'control group' depending on the zip codes.	Hospital data ASZ and dataset population combined	All
Calculate the total hospital expenditures per age group by dividing the total costs per group per year with the population per age group.	Hospital data ASZ and dataset population combined	Total hospital expenditures
Calculate the total fall incidents per age group by dividing the total costs per group per year with the population per age group.	Hospital data ASZ and dataset population combined	Total fall incidents
Visualize the distribution of the severity of the fall incidents per group and per age group.	Hospital data ASZ and dataset population combined	Severity of fall incidents
Apply the Difference in Differences method and use the formula in section 5.2.2.	Hospital data ASZ and dataset population combined	Total hospital expenditures
Visualize results in Ploty	Hospital data ASZ and dataset population combined	All

Appendix C: Demographic data

In table 12, the population of older adults per region can be found (Central Bureau of Statistics, 2017).

Table 12: Total population of older adults per region

Year	Age group	Region			
		Dordrecht-East	Dordrecht-West	Sliedrecht	Zwijndrecht
2014	65-75	6.700	3.830	1.775	4.645
	75-85	4.175	1.590	1.110	2.830
	85+	1.655	675	490	1.050
2015	65-75	6.855	4.015	1.760	4.740
	75-85	4.215	1.645	1.155	2.885
	85+	1.765	635	510	1.105
2016	65-75	7.090	4.150	1.760	4.825
	75-85	4.290	1.770	1.180	2.915
	85+	1.780	605	535	1.140
2017	65-75	7.200	4.280	1.790	4.900
	75-85	4.340	1.795	1.160	2.920
	85+	1.815	605	550	1.145

This analysis focusses on community-dwelling elderly. In the next table, the percentages of elderly living in a nursing home per age group are shown (Central Bureau of Statistics, 2018).

Table 13: Percentages of elderly living in a nursing home per age group and year

Age group	2014	2015	2016	2017	2018
65-75	1.12%	1.10%	1.13%	1.05%	1.11%
75-85	4.80%	4.31%	4.12%	3.74%	3.76%
85+	22.75%	20.95%	20.01%	18.50%	18.50%

When decreasing the population of table 12 using the percentages of table 13, the total number of community-dwelling elderly per age group and region can be calculated. These numbers can be found in table 14 and are used in the analyses to assess the effect of fall prevention programs.

Table 14: The total number of community-dwelling elderly per age group and region

Year	Age group	Region			
		Dordrecht-East	Dordrecht-West	Sliedrecht	Zwijndrecht
2014	65-75	6.625	3.788	1.755	4.592
	75-85	3.974	1.514	1.057	2.694
	85+	1.278	522	379	811
2015	65-75	6.780	3.971	1.740	4.687
	75-85	4.034	1.574	1.105	2.761
	85+	1.395	502	403	872
2016	65-75	7.009	4.104	1.740	4.771
	75-85	4.112	1.697	1.131	2.796
	85+	1.424	484	428	912
2017	65-75	7.123	4.235	1.771	4.848
	75-85	4.178	1.728	1.117	2.811
	85+	1.478	494	448	934

Appendix D: Testing pre-intervention trends of hospital expenditures

In this test, the DID method is used to determine whether there is a difference in the trends between the groups in the pre-intervention years (described in section 4.2.3).

In table 15, the WLS-regression results are presented to investigate whether the CTA holds between year 2015-2016 and 2016-2017. The table containing the data used to conduct this analysis can be found in Appendix E4.

Table 15: CTA test results - year 15-16 and 16-17 (hospital expenditures)

Dep. Variable:	CTA_Test_1516_1617_Costs_per_Elderly	R-squared:	0.215			
Model:	WLS	Adj. R-squared:	0.136			
Method:	Least Squares	F-statistic:	2.732			
Date:	Sun, 30 Jun 2019	Prob (F-statistic):	0.0422			
Time:	12:05:54	Log-Likelihood:	-188.26			
No. Observations:	45	AIC:	386.5			
Df Residuals:	40	BIC:	395.5			
Df Model:	4					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.05	0.95]
const	60.7486	4.911	12.371	0.000	52.480	69.017
Ig	6.4358	6.068	1.061	0.295	-3.782	16.654
P1t	-0.0577	5.962	-0.010	0.992	-10.097	9.982
P2t	-13.9403	7.275	-1.916	0.062	-26.190	-1.691
Ig * P2t	17.3696	10.378	1.674	0.102	-0.105	34.844

The coefficient of Ig * P2t is positive and has a low p-value (0.10). This indicates that there is a difference in the trend between the control- and intervention group in a pre-intervention period. Therefore, the CTA does not hold and the DID method cannot be used to assess the effect of fall prevention programs on the hospital expenditures.

Appendix E: Data used to perform DID analyses

Appendix E1: Data used to test the CTA for the number of falls in year 14-15 & 15-16

Table 16: Data used to test the CTA for the number of falls in year 14-15 & 15-16

PC4	Analysis_Year	# falls / 100 elderly	Ig	P1t	Ig * P1t	Population
3311	2014-2015	3.041	0	0	0	2335
3312	2014-2015	3.775	0	0	0	1139
3314	2014-2015	3.993	0	0	0	1828
3315	2014-2015	3.018	1	0	0	1922
3317	2014-2015	6.019	1	0	0	2243
3318	2014-2015	2.699	1	0	0	1445
3319	2014-2015	4.283	1	0	0	2218
3328	2014-2015	3.284	1	0	0	2771
3331	2014-2015	3.157	0	0	0	1584
3332	2014-2015	3.686	0	0	0	2659
3333	2014-2015	3.134	0	0	0	989
3334	2014-2015	2.604	0	0	0	1344
3335	2014-2015	2.254	0	0	0	710
3361	2014-2015	3.045	0	0	0	821
3362	2014-2015	3.516	0	0	0	1991
3311	2015-2016	3.293	0	1	0	2460
3312	2015-2016	3.128	0	1	0	1215
3314	2015-2016	3.422	0	1	0	1870
3315	2015-2016	3.863	1	1	1	2019
3317	2015-2016	3.715	1	1	1	2234
3318	2015-2016	3.462	1	1	1	1473
3319	2015-2016	4.708	1	1	1	2209
3328	2015-2016	3.821	1	1	1	2879
3331	2015-2016	3.066	0	1	0	1631
3332	2015-2016	3.689	0	1	0	2684
3333	2015-2016	3.21	0	1	0	997
3334	2015-2016	2.246	0	1	0	1380
3335	2015-2016	1.984	0	1	0	756
3361	2015-2016	4.509	0	1	0	865
3362	2015-2016	2.778	0	1	0	1980

Appendix E2: Data used to test the CTA for the number of falls in year 15-16 & 16-17

Table 17: Data used to test the CTA for the number of falls in year 15-16 & 16-17

PC4	Analysis_Year	# falls / 100 elderly	Ig	P1t	P2t	Ig * P2t	Population
3311	2014-2015	3.041	0	0	0	0	2335
3312	2014-2015	3.775	0	0	0	0	1139
3314	2014-2015	3.993	0	0	0	0	1828
3315	2014-2015	3.018	1	0	0	0	1922
3317	2014-2015	6.019	1	0	0	0	2243
3318	2014-2015	2.699	1	0	0	0	1445
3319	2014-2015	4.283	1	0	0	0	2218
3328	2014-2015	3.284	1	0	0	0	2771
3331	2014-2015	3.157	0	0	0	0	1584
3332	2014-2015	3.686	0	0	0	0	2659
3333	2014-2015	3.134	0	0	0	0	989
3334	2014-2015	2.604	0	0	0	0	1344
3335	2014-2015	2.254	0	0	0	0	710
3361	2014-2015	3.045	0	0	0	0	821
3362	2014-2015	3.516	0	0	0	0	1991
3311	2015-2016	3.293	0	1	0	0	2460
3312	2015-2016	3.128	0	1	0	0	1215
3314	2015-2016	3.422	0	1	0	0	1870
3315	2015-2016	3.863	1	1	0	0	2019
3317	2015-2016	3.715	1	1	0	0	2234
3318	2015-2016	3.462	1	1	0	0	1473
3319	2015-2016	4.708	1	1	0	0	2209
3328	2015-2016	3.821	1	1	0	0	2879
3331	2015-2016	3.066	0	1	0	0	1631
3332	2015-2016	3.689	0	1	0	0	2684
3333	2015-2016	3.21	0	1	0	0	997
3334	2015-2016	2.246	0	1	0	0	1380
3335	2015-2016	1.984	0	1	0	0	756
3361	2015-2016	4.509	0	1	0	0	865
3362	2015-2016	2.778	0	1	0	0	1980
3311	2016-2017	2.642	0	0	1	0	2612
3312	2016-2017	2.41	0	0	1	0	1245
3314	2016-2017	2.212	0	0	1	0	1944
3315	2016-2017	2.719	1	0	1	1	2133
3317	2016-2017	3.881	1	0	1	1	2319
3318	2016-2017	3.441	1	0	1	1	1453
3319	2016-2017	3.796	1	0	1	1	2239
3328	2016-2017	3.527	1	0	1	1	2977
3331	2016-2017	2.786	0	0	1	0	1687
3332	2016-2017	3.095	0	0	1	0	2682
3333	2016-2017	2.906	0	0	1	0	998
3334	2016-2017	3.022	0	0	1	0	1390
3335	2016-2017	2.963	0	0	1	0	810
3361	2016-2017	3.072	0	0	1	0	944
3362	2016-2017	2.802	0	0	1	0	1927

Appendix E3: Data used to determine effect of programs on the number of falls

Table 18: Data used to determine effect of programs on the number of falls

PC4	Analysis_Year	# falls / 100 elderly	Ig	P1t	P2t	P3t	Ig * P3t	Population
3311	2014-2015	3.041	0	0	0	0	0	2335
3312	2014-2015	3.775	0	0	0	0	0	1139
3314	2014-2015	3.993	0	0	0	0	0	1828
3315	2014-2015	3.018	1	0	0	0	0	1922
3317	2014-2015	6.019	1	0	0	0	0	2243
3318	2014-2015	2.699	1	0	0	0	0	1445
3319	2014-2015	4.283	1	0	0	0	0	2218
3328	2014-2015	3.284	1	0	0	0	0	2771
3331	2014-2015	3.157	0	0	0	0	0	1584
3332	2014-2015	3.686	0	0	0	0	0	2659
3333	2014-2015	3.134	0	0	0	0	0	989
3334	2014-2015	2.604	0	0	0	0	0	1344
3335	2014-2015	2.254	0	0	0	0	0	710
3361	2014-2015	3.045	0	0	0	0	0	821
3362	2014-2015	3.516	0	0	0	0	0	1991
3311	2015-2016	3.293	0	1	0	0	0	2460
3312	2015-2016	3.128	0	1	0	0	0	1215
3314	2015-2016	3.422	0	1	0	0	0	1870
3315	2015-2016	3.863	1	1	0	0	0	2019
3317	2015-2016	3.715	1	1	0	0	0	2234
3318	2015-2016	3.462	1	1	0	0	0	1473
3319	2015-2016	4.708	1	1	0	0	0	2209
3328	2015-2016	3.821	1	1	0	0	0	2879
3331	2015-2016	3.066	0	1	0	0	0	1631
3332	2015-2016	3.689	0	1	0	0	0	2684
3333	2015-2016	3.21	0	1	0	0	0	997
3334	2015-2016	2.246	0	1	0	0	0	1380
3335	2015-2016	1.984	0	1	0	0	0	756
3361	2015-2016	4.509	0	1	0	0	0	865
3362	2015-2016	2.778	0	1	0	0	0	1980
3311	2016-2017	2.642	0	0	1	0	0	2612
3312	2016-2017	2.41	0	0	1	0	0	1245
3314	2016-2017	2.212	0	0	1	0	0	1944
3315	2016-2017	2.719	1	0	1	0	0	2133
3317	2016-2017	3.881	1	0	1	0	0	2319
3318	2016-2017	3.441	1	0	1	0	0	1453
3319	2016-2017	3.796	1	0	1	0	0	2239
3328	2016-2017	3.527	1	0	1	0	0	2977
3331	2016-2017	2.786	0	0	1	0	0	1687
3332	2016-2017	3.095	0	0	1	0	0	2682
3333	2016-2017	2.906	0	0	1	0	0	998
3334	2016-2017	3.022	0	0	1	0	0	1390
3335	2016-2017	2.963	0	0	1	0	0	810
3361	2016-2017	3.072	0	0	1	0	0	944
3362	2016-2017	2.802	0	0	1	0	0	1927
3311	2017-2018	2.546	0	0	0	1	0	2710
3312	2017-2018	2.108	0	0	0	1	0	1281
3314	2017-2018	2.738	0	0	0	1	0	1972
3315	2017-2018	2.726	1	0	0	1	1	2201
3317	2017-2018	3.24	1	0	0	1	1	2315
3318	2017-2018	3.112	1	0	0	1	1	1446
3319	2017-2018	3.662	1	0	0	1	1	2239
3328	2017-2018	2.548	1	0	0	1	1	3100
3331	2017-2018	3.009	0	0	0	1	0	1695
3332	2017-2018	3.558	0	0	0	1	0	2698
3333	2017-2018	2.888	0	0	0	1	0	1004
3334	2017-2018	2.967	0	0	0	1	0	1382
3335	2017-2018	1.932	0	0	0	1	0	880
3361	2017-2018	3.138	0	0	0	1	0	956
3362	2017-2018	2.588	0	0	0	1	0	1932

Appendix E4: Data used to test the CTA for hospital expenditures in year 15-16 & 16-17

Table 19: Data used to test the CTA for hospital expenditures in year 15-16 & 16-17

PC4	Analysis_Year	Hosp. costs / elderly	Ig	P1t	P2t	Ig * P2t	Population
3311	2014-2015	45.863	0	0	0	0	2335
3312	2014-2015	78.481	0	0	0	0	1139
3314	2014-2015	49.33	0	0	0	0	1828
3315	2014-2015	50.206	1	0	0	0	1922
3317	2014-2015	92.011	1	0	0	0	2243
3318	2014-2015	53.457	1	0	0	0	1445
3319	2014-2015	57.786	1	0	0	0	2218
3328	2014-2015	59.201	1	0	0	0	2771
3331	2014-2015	58.428	0	0	0	0	1584
3332	2014-2015	88.116	0	0	0	0	2659
3333	2014-2015	79.869	0	0	0	0	989
3334	2014-2015	66.782	0	0	0	0	1344
3335	2014-2015	44.711	0	0	0	0	710
3361	2014-2015	65.926	0	0	0	0	821
3362	2014-2015	53.822	0	0	0	0	1991
3311	2015-2016	55.78	0	1	0	0	2460
3312	2015-2016	59.062	0	1	0	0	1215
3314	2015-2016	63.949	0	1	0	0	1870
3315	2015-2016	63.722	1	1	0	0	2019
3317	2015-2016	48.588	1	1	0	0	2234
3318	2015-2016	74.745	1	1	0	0	1473
3319	2015-2016	101.256	1	1	0	0	2209
3328	2015-2016	67.622	1	1	0	0	2879
3331	2015-2016	55.497	0	1	0	0	1631
3332	2015-2016	69.011	0	1	0	0	2684
3333	2015-2016	33.385	0	1	0	0	997
3334	2015-2016	33.21	0	1	0	0	1380
3335	2015-2016	58.75	0	1	0	0	756
3361	2015-2016	128.197	0	1	0	0	865
3362	2015-2016	41.79	0	1	0	0	1980
3311	2016-2017	48.367	0	0	1	0	2612
3312	2016-2017	48.422	0	0	1	0	1245
3314	2016-2017	26.15	0	0	1	0	1944
3315	2016-2017	56.167	1	0	1	1	2133
3317	2016-2017	70.996	1	0	1	1	2319
3318	2016-2017	64.735	1	0	1	1	1453
3319	2016-2017	83.068	1	0	1	1	2239
3328	2016-2017	74.169	1	0	1	1	2977
3331	2016-2017	44.114	0	0	1	0	1687
3332	2016-2017	51.911	0	0	1	0	2682
3333	2016-2017	51.608	0	0	1	0	998
3334	2016-2017	44.169	0	0	1	0	1390
3335	2016-2017	61.772	0	0	1	0	810
3361	2016-2017	45.344	0	0	1	0	944
3362	2016-2017	53.596	0	0	1	0	1927

Appendix F: Selection and classification of the diagnoses related to fall incidents

In the table below, the relevant diagnoses have been classified. This has been done in accordance with Emergency Physician Annemarie van der Velden (Van der Velden, interview 1, 2019; Van der Velden, interview 2, 2019). The classification per DOT can be found in the excel 'Selection relevant diagnoses and classification of DOTs'. The prices of the DOTs have been determined based on the prices of the Nederlandse Zorgautoriteit (NZa) (open) database (Nederlandse Zorgautoriteit, 2018). As the NZa database is not complete, a few prices of combinations of diagnosis and DOT-codes are unknown. In that case, the prices of the Dimenzion system are used (prices of the ASZ). See the excel for more details.

According to Emergency Physician Annemarie van der Velden, there is not a single hip fracture which is not treated directly in a hospital (Van der Velden, interview 2, 2019). The patients with these ambulatory DOTs are often transferred to another hospital and treated for their hip at that same location. Therefore, the ambulatory care DOTs of this diagnosis have classification 6.

Table 20: Selection and classification of the diagnoses related to falls

	Classification 1	Classification 2	Classification 3	Classification 4	Classification 5	Classification 6
Description	Contusions and minor injuries on head. Ambulatory care DOTs only.	Contusions and minor injuries on head. Patient stays overnight (inpatient care only).	All relevant fractures. Ambulatory care only. Ambulant Femur is excluded and has classification 6.	Fractures with moderate consequences. Surgery is needed and patient stays overnight (inpatient care DOTs only).	Fractures with major consequences. Surgery is needed and patient stays overnight (inpatient care DOTs only).	Fractures with a very high impact on the life of the elderly (often death within a year). Surgery is needed and patient stays overnight (inpatient care DOTs only).
Diagnoses	- Overig letsel hoofd - Commotio / contusio cerebri - (Contusie) enkelvoudig - (Contusie) multiple	- Overig letsel hoofd - Commotio / contusio cerebri - (Contusie) enkelvoudig - (Contusie) multiple	- All fractures listed under classification 4,5 and 6.	- Pols - Falangen van de voet - Olecranon - Radiuskop - Onderarm - Carpus - Metacarpalia - Falangen van de hand - Schouder - Clavicula - Metatarsalia - Aangezichtsbeenderen / kaak	- Wervelkolom - Scapula - Humerus - Distale humerus - Ribben - Bekken - Enkel - Calcaneus	- Femur - Femur overig - Tibia - Acetabulum - Tibiaplateau - Patella

Appendix G: Python code

```
1. # Python tool to assess the effectiveness of fall-prevention programs using hospital data
2. ## Case study in Dordrecht (Netherlands)
3. ### 1st of July 2019
4. ##### Joost van Berckel (Student number: 4258037)
5. ##### Part of thesis: 'Preventing falls among the community-dwelling elderly'
6.
7. # Data preparation and cleaning
8.
9. ### Preparing the ASZ hospital dataset and merge zip code dataset and 'Cost- and classification' dataset
10.
11. # Import the libraries needed to clean the data and to conduct the analysis.
12.
13. import pandas as pd
14. import numpy as np
15. import matplotlib.pyplot as plt
16. import geopandas as gp
17. import seaborn as sns
18. %matplotlib inline
19.
20. pd.set_option('display.max_columns', 50)
21.
22. # Load the raw Albert Schweitzer Hospital data containing all Emergency Room (ER) registrations from the last 5 years.
23.
24. Elderly_ERvisits_Raw = pd.read_csv('Datasets_csv/190108_elderly_visits_ER.csv',
25.                                     sep=',',
26.                                     encoding='ISO-8859-1',
27.                                     parse_dates=['Datum', 'BegindatumDBC', 'EinddatumDBC', 'Overlijdensdatum'],
28.                                     dayfirst=True)
29.
30. # Delete unwanted columns.
31.
32. Elderly_ERvisits_Raw = Elderly_ERvisits_Raw.drop(['AANTAL',
33.                                                 'REFNUMMER',
34.                                                 'DBCnummer',
35.                                                 'Zorgproductomschrijving',
36.                                                 'Zorgproductomschrijving2'], axis=1)
37.
38. # Rename columns.
39.
```

```

40. Elderly_ERvisits_Raw.columns = ['ID',
41.                                     'Date_in_System',
42.                                     'Patient_Number',
43.                                     'Age',
44.                                     'Episode',
45.                                     'Diagnosis_Number',
46.                                     'Diagnosis_Description',
47.                                     'DOT_Code',
48.                                     'DOT_Type',
49.                                     'Startdate_DOT',
50.                                     'Enddate_DOT',
51.                                     'Sex',
52.                                     'Zip_Code',
53.                                     'Death_Date',
54.                                     'Department',
55.                                     'Living_Situation',
56.                                     'Living_Situation_Discharge']
57.
58.
59. # Check if dates are parsed correctly.
60.
61. check = Elderly_ERvisits_Raw['Enddate_DOT']-Elderly_ERvisits_Raw['Startdate_DOT']
62. # check.head(50)
63.
64. # Check shape: first number is rows, second number is columns.
65.
66. Elderly_ERvisits_Raw.shape
67.
68. # Load costs and classifications of the relevant diagnoses. See excel file 'Selection relevant diagnoses and classification'
69. # for additional information on how these diagnoses have been selected and classified. This was done in accordance with
70. # emergency physician Annemarie van der Velden. Data about the costs of DOTs is retrieved from the open data source of the
71. # Dutch Healthcare Authority (NZA) (Nederlandse Zorgautoriteit, 2018).
72.
73. Cost_and_classification_DOTs_Raw = pd.read_csv('Datasets_csv/190318_Cost_and_classification_DOTs.csv',
74.                                                 sep=',',
75.                                                 encoding='ISO-8859-1')
76.
77. # Delete unwanted columns.
78.
79. Cost_and_classification_DOTs = Cost_and_classification_DOTs_Raw.drop(['Department',
80.                                         'Diagnosis number',
81.                                         'Diagnoses in category: "Letsel"'],

```

```

82.                                         'DBC description short',
83.                                         'Total number of products in HiX data in last 5 years'],
84.                                         axis=1)
85.
86. # Rename columns.
87.
88. Cost_and_classification_DOTs.columns = ['DiagnosisCode_plus_DiagnosisDescription',
89.                                         'DOT_Code',
90.                                         'Cost_DOT_Dimension',
91.                                         'Cost_DOT_NZA',
92.                                         'Final_DOT_Cost',
93.                                         'Classification']
94.
95. # Create extra column with the diagnosis-code plus description.
96.
97. Elderly_ERvisits_Raw['DiagnosisCode_plus_DiagnosisDescription'] = Elderly_ERvisits_Raw['Diagnosis_Number'] + ", " +\
98.                                         Elderly_ERvisits_Raw['Diagnosis_Description']
99.
100. # Keep only the rows with the fractures related to fall incidents. These can be found in the 'Cost and Classification' dataset.
101.
102. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Raw[
103.                                         Elderly_ERvisits_Raw['DiagnosisCode_plus_DiagnosisDescription'].isin(Cost_and_classification_DOTs['DiagnosisCode_plus_DiagnosisDescription'].unique())]
104.
105.
106. # Check if the same number of unique diagnoses are present in the dataset.
107.
108. print(Cost_and_classification_DOTs.DiagnosisCode_plus_DiagnosisDescription.nunique())
109. print(Elderly_ERvisits_Relevant_Diagnoses.DiagnosisCode_plus_DiagnosisDescription.nunique())
110.
111.
112. # The following code is used to remove duplicate registrations. Just to be clear: patients with multiple fractures after a
113. # fall have several DOTs registered on the same day, these registrations will not be deleted.
114.
115. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop_duplicates(
116.                                         subset=['Startdate_DOT',
117.                                         'Patient_Number',
118.                                         'DiagnosisCode_plus_DiagnosisDescription',
119.                                         'DOT_Code'])
120.
121. # Drop the DOTs created in 2013.
122.

```

```

123. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses[Elderly_ERvisits_Relevant_Diagnoses.
124.                                         Startdate_DOT >= '2014-01-01']
125.
126. # Drop DOTs with elderly who died before the first of January 2014 (this case: one person).
127.
128. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
129.                                         Elderly_ERvisits_Relevant_Diagnoses.Death_Date <= '2014-01-01'].index)
130.
131. # Check shape: first number is rows, second number is columns.
132.
133. Elderly_ERvisits_Relevant_Diagnoses.shape
134.
135. # Drop the DOTs of older adults living in a nursing home, because this analysis focusses on community-dwelling elderly.
136.
137. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
138.                                         Elderly_ERvisits_Relevant_Diagnoses.Living_Situation == 'Verpleeg-/verzorgingshuis'].index)
139.
140. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
141.                                         Elderly_ERvisits_Relevant_Diagnoses.Living_Situation == 'Instelling (anders)'].index)
142.
143. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
144.                                         Elderly_ERvisits_Relevant_Diagnoses.Living_Situation == 'Instelling (revalidatie)'].index)
145.
146. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
147.                                         Elderly_ERvisits_Relevant_Diagnoses.Living_Situation == 'Instelling (psychiatrisch)'].index)
148.
149. # Check shape: first number is rows, second number is columns.
150.
151. Elderly_ERvisits_Relevant_Diagnoses.shape
152.
153. # Another problem with the data is that some of the DOT-codes are missing. These patients did get a diagnosis (in total:
154. # 518 patients), but not a DOT. The DOT code with the lowest costs and severity (often the 'Ambulant light'-
155. DOT) has to replace
156. # these missing values.
157.
158. # Replace the missing DOT-codes of diagnosis '1402, Commotio / contusio cerebri' to DOT-code 199299011.
159. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
160.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] ==
161.                                         '1402, Commotio / contusio cerebri'), 'DOT_Code'] = 199299011
162.
163. # Replace the missing DOT-codes of diagnosis '1409, Overig letsel hoofd' to DOT-code 199299011.

```

```

164. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
165.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
166.                                         '1409, Overig letsel hoofd'), 'DOT_Code'] = 199299011
167.
168.
169. # Replace the missing DOT-codes of diagnosis '3019, Femur proximaal (+collum)' to DOT-code 199299015.
170.
171. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
172.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
173.                                         '3019, Femur proximaal (+collum)'), 'DOT_Code'] = 199299015
174.
175. # Replace the missing DOT-codes of diagnosis '218, Femur, proximaal (+ collum)' to DOT-code 199299015.
176.
177. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
178.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
179.                                         '218, Femur, proximaal (+ collum)'), 'DOT_Code'] = 199299015
180.
181. # Replace the missing DOT-codes of diagnosis '3020, Femur overig' to DOT-code 199299028.
182.
183. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
184.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
185.                                         '3020, Femur overig'), 'DOT_Code'] = 199299028
186.
187. # Replace the missing DOT-codes of diagnosis '209, Olecranon' to DOT-code 199299028.
188.
189. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
190.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
191.                                         '209, Olecranon'), 'DOT_Code'] = 199299028
192.
193. # Replace the missing DOT-codes of diagnosis '236, Calcaneus' to DOT-code 199299119. As there is no 'ambulant light'-DOT,
194. # these missing DOT-Codes are converted to a 'ambulant-middel'-DOT.
195.
196. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
197.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
198.                                         '236, Calcaneus'), 'DOT_Code'] = 199299119
199.
200. # Replace the missing DOT-codes of diagnosis '221, Tibiaplateau' to DOT-code 199299119. As there is no 'ambulant light'-DOT,
201. # these missing DOT-Codes are converted to a 'ambulant-middel'-DOT.
202.
203. Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull() &
204.                                         (Elderly_ERvisits_Relevant_Diagnoses['DiagnosisCode_plus_DiagnosisDescription'] == 
205.                                         '221, Tibiaplateau'), 'DOT_Code'] = 199299119

```

```

206.      # Replace the missing DOT-codes of the rest of the diagnoses to code 199299120.
207.      Elderly_ERvisits_Relevant_Diagnoses.loc[Elderly_ERvisits_Relevant_Diagnoses['DOT_Code'].isnull(),'DOT_Code'] = 199299120
208.
209.
210.      # Check if there are any missing values left in the column 'DOT_Code'.
211.
212.      Elderly_ERvisits_Relevant_Diagnoses.DOT_Code.isnull().sum()
213.
214.
215.      # Combine the two datasets to add classification (severity 1 to 6) and costs to the DOTs in the main dataset.
216.
217.      Elderly_ERvisits_Relevant_Diagnoses = pd.merge(Elderly_ERvisits_Relevant_Diagnoses,
218.                                                       Cost_and_classification_DOTs,
219.                                                       how='left')
220.
221.      # Check if there are any missing values in the column 'Classification'
222.
223.      print(Elderly_ERvisits_Relevant_Diagnoses.Classification.isnull().sum())
224.
225.      # Check if there are any missing values in the column 'Final_DOT_Cost'
226.
227.      print(Elderly_ERvisits_Relevant_Diagnoses.Final_DOT_Cost.isnull().sum())
228.
229.      # Check shape: first number is rows, second number is columns.
230.
231.      Elderly_ERvisits_Relevant_Diagnoses.shape
232.
233.      # Load file with Dutch zip-codes and their locations (Imergis, 2019).
234.
235.      Zip_Codes_And_Locations = pd.read_csv('Datasets_csv/190319_Zip_Codes_And_Locations.csv',
236.                                              sep=',',
237.                                              encoding='ISO-8859-1')
238.
239.      # Delete unwanted columns.
240.
241.      Zip_Codes_And_Locations = Zip_Codes_And_Locations.drop(['woonplaatscode',
242.                                                               'gemeentecode',
243.                                                               'woonplaatsnaam',
244.                                                               'provinciecode',
245.                                                               'waterschapnaam',
246.                                                               'politie-eenheid',
247.                                                               'omgevingsdienst'],

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248.                                         'drinkwater',
249.                                         'netbeheer'], axis=1)
250.
251. # Rename columns.
252.
253. Zip_Codes_And_Locations.columns = ['Zip_Code',
254.                                     'CBS_District_Name',
255.                                     'CBS_Neighborhood_Name',
256.                                     'Municipality',
257.                                     'Province',
258.                                     'Area',
259.                                     'rdx',
260.                                     'rdy']
261.
262. # Make sure that there is no space between the four numbers and the two letters of the zip-codes.
263.
264. Elderly_ERvisits_Relevant_Diagnoses['Zip_Code'] = Elderly_ERvisits_Relevant_Diagnoses['Zip_Code'].str.replace(" ","")
265.
266. # Merge the dataset with the zipcodes and their locations.
267.
268. Elderly_ERvisits_Relevant_Diagnoses = pd.merge(Elderly_ERvisits_Relevant_Diagnoses,
269.                                                 Zip_Codes_And_Locations,
270.                                                 how='left')
271.
272. # Check shape: first number is rows, second number is columns.
273.
274. Elderly_ERvisits_Relevant_Diagnoses.shape
275.
276. # Check for any missing municipalities.
277.
278. Elderly_ERvisits_Relevant_Diagnoses.Municipality.isnull().sum()
279.
280. # Drop the rows with wrong zip-codes and therefore missing values (48 rows).
281.
282. Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
283. Elderly_ERvisits_Relevant_Diagnoses.Municipality.isnull()].index)
284.
285. # Add a column with only the first 4 digits of the zip codes (PC4: Post code 4).
286.
287. Elderly_ERvisits_Relevant_Diagnoses['PC4'] = Elderly_ERvisits_Relevant_Diagnoses['Zip_Code'].str[:4]
288.
289. # Drop rows with missing values in column "PC4".

```

```

290.
291.     Elderly_ERvisits_Relevant_Diagnoses = Elderly_ERvisits_Relevant_Diagnoses.drop(Elderly_ERvisits_Relevant_Diagnoses[
292.                                         Elderly_ERvisits_Relevant_Diagnoses.PC4.isnull()].index)
293.
294.     # Add a column with number of DOTs (which is always 1) to be able to sum the DOTs.
295.
296.     Elderly_ERvisits_Relevant_Diagnoses[ 'Number_of_DOTs' ] = 1
297.
298.     # Add column with the year of the startdate of the DOT.
299.
300.     Elderly_ERvisits_Relevant_Diagnoses[ 'DOT_Year' ]=Elderly_ERvisits_Relevant_Diagnoses[ 'Startdate_DOT' ].dt.year
301.
302.     # Add a column indicating the age categories of the patients. The following age-groups have been chosen:
303.     # 65-75, 75-85 and 85+.
304.
305.     def assign_age_groups(age):
306.         if age < 75:
307.             return '65-75'
308.         elif ((age >= 75) & (age < 85)):
309.             return '75-85'
310.         elif age >= 85:
311.             return '85+'
312.
313.     Elderly_ERvisits_Relevant_Diagnoses[ 'Age_Group' ] = Elderly_ERvisits_Relevant_Diagnoses[ 'Age' ].apply(assign_age_groups)
314.
315.     Elderly_ERvisits_Relevant_Diagnoses.shape
316.
317.     # Add a column indicating a period of three months. The data has been requested in january 2019, so the data of the last
318.     # three months of 2018 are not reliable. Many DOTs in this month do not have an end-date. The following time periods have
319.     # been chosen: winter is December, January, February; spring is March, April, May; summer is June, July, August; Autumn is
320.     # September, October, November. Because of these time periods, the first two months of 2014 will not be used.
321.
322.     def assign_period(date):
323.         if ((date >= pd.to_datetime('2014-01-01')) & (date < pd.to_datetime('2014-03-01'))):
324.             return 'NOT_COMPLETE_PERIOD_Winter2014'
325.         elif ((date >= pd.to_datetime('2014-03-01')) & (date < pd.to_datetime('2014-06-01'))):
326.             return '03/14-05/14'
327.         elif ((date >= pd.to_datetime('2014-06-01')) & (date < pd.to_datetime('2014-09-01'))):
328.             return '06/14-08/14'
329.         elif ((date >= pd.to_datetime('2014-09-01')) & (date < pd.to_datetime('2014-12-01'))):
330.             return '09/14-11/14'
331.         elif ((date >= pd.to_datetime('2014-12-01')) & (date < pd.to_datetime('2015-03-01'))):

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```

332.         return '12/14-02/15'
333.
334.     elif ((date >= pd.to_datetime('2015-03-01')) & (date < pd.to_datetime('2015-06-01'))):
335.         return '03/15-05/15'
336.     elif ((date >= pd.to_datetime('2015-06-01')) & (date < pd.to_datetime('2015-09-01'))):
337.         return '06/15-08/15'
338.     elif ((date >= pd.to_datetime('2015-09-01')) & (date < pd.to_datetime('2015-12-01'))):
339.         return '09/15-11/15'
340.     elif ((date >= pd.to_datetime('2015-12-01')) & (date < pd.to_datetime('2016-03-01'))):
341.         return '12/15-02/16'
342.
343.     elif ((date >= pd.to_datetime('2016-03-01')) & (date < pd.to_datetime('2016-06-01'))):
344.         return '03/16-05/16'
345.     elif ((date >= pd.to_datetime('2016-06-01')) & (date < pd.to_datetime('2016-09-01'))):
346.         return '06/16-08/16'
347.     elif ((date >= pd.to_datetime('2016-09-01')) & (date < pd.to_datetime('2016-12-01'))):
348.         return '09/16-11/16'
349.     elif ((date >= pd.to_datetime('2016-12-01')) & (date < pd.to_datetime('2017-03-01'))):
350.         return '12/16-02/17'
351.
352.     elif ((date >= pd.to_datetime('2017-03-01')) & (date < pd.to_datetime('2017-06-01'))):
353.         return '03/17-05/17'
354.     elif ((date >= pd.to_datetime('2017-06-01')) & (date < pd.to_datetime('2017-09-01'))):
355.         return '06/17-08/17'
356.     elif ((date >= pd.to_datetime('2017-09-01')) & (date < pd.to_datetime('2017-12-01'))):
357.         return '09/17-11/17'
358.     elif ((date >= pd.to_datetime('2017-12-01')) & (date < pd.to_datetime('2018-03-01'))):
359.         return '12/17-02/18'
360.
361.     elif ((date >= pd.to_datetime('2018-03-01')) & (date < pd.to_datetime('2018-06-01'))):
362.         return '03/18-05/18'
363.     elif ((date >= pd.to_datetime('2018-06-01')) & (date < pd.to_datetime('2018-09-01'))):
364.         return '06/18-08/18'
365.     elif ((date >= pd.to_datetime('2018-09-01')) & (date < pd.to_datetime('2018-12-01'))):
366.         return 'Unreliable_data'
367.     elif ((date >= pd.to_datetime('2018-12-01')) & (date < pd.to_datetime('2019-03-01'))):
368.         return 'Unreliable_data'
369. # With more data, these last two lines can be used to assign a period for the winter 2018/2019.
370.
371. # Apply definition to assign a period.
372.
```

```

373. Elderly_ERvisits_Relevant_Diagnoses['Time_Period'] = Elderly_ERvisits_Relevant_Diagnoses['Startdate_DOT'].apply(assign_period)
374.
375. # In the following code, the year of analysis will be defined. The data is reliable until the autumn of 2018 and the fall
376. # prevention programs started in March 2017. It will take 6 months before the programs will have an effect on the number
377. # (and costs) of fall incidents. Therefore, the following years will be compared with one another: from September of year x
378. # until September of the next year.
379.
380. def analysis_year(date):
381.     if ((date >= pd.to_datetime('2014-01-01')) & (date < pd.to_datetime('2014-09-01'))):
382.         return 'NOT_COMPLETE_PERIOD_Winter2014'
383.     elif ((date >= pd.to_datetime('2014-09-01')) & (date < pd.to_datetime('2015-09-01'))):
384.         return '2014-2015'
385.     elif ((date >= pd.to_datetime('2015-09-01')) & (date < pd.to_datetime('2016-09-01'))):
386.         return '2015-2016'
387.     elif ((date >= pd.to_datetime('2016-09-01')) & (date < pd.to_datetime('2017-09-01'))):
388.         return '2016-2017'
389.     elif ((date >= pd.to_datetime('2017-09-01')) & (date < pd.to_datetime('2018-09-01'))):
390.         return '2017-2018'
391.     elif ((date >= pd.to_datetime('2018-09-01')) & (date < pd.to_datetime('2019-09-01'))):
392.         return 'Unreliable'
393.
394. Elderly_ERvisits_Relevant_Diagnoses['Analysis_Year'] = Elderly_ERvisits_Relevant_Diagnoses['Startdate_DOT'].apply(analysis_year)
395.
396. # Add a column indicating the season (Summer, Autumn, Winter, Spring).
397.
398. Elderly_ERvisits_Relevant_Diagnoses['Time_Period_Season'] = np.where(Elderly_ERvisits_Relevant_Diagnoses['Time_Period'].str.startswith('03'), 'Spring',
399.                                         np.where(Elderly_ERvisits_Relevant_Diagnoses['Time_Period'].str.startswith('06'), 'Summer',
400.                                         np.where(Elderly_ERvisits_Relevant_Diagnoses['Time_Period'].str.startswith('09'), 'Autumn',
401.                                         np.where(Elderly_ERvisits_Relevant_Diagnoses['Time_Period'].str.startswith('12'), 'Winter', 0))))
402.
403.
404.
405.
406.
407. # Check shape: first number is rows, second number is columns.
408.
409. Elderly_ERvisits_Relevant_Diagnoses.shape
410.
411. # Data cleaning is done at this point. Save a new dataframe for the analysis of the total cost.
412.

```

```

413.     Cleaned_ER_DOTS = Elderly_ERvisits_Relevant_Diagnoses
414.
415.     # It is possible that an older adult has multiple fractures after a fall. To analyse the severity of the fall or the total
416.     # number of injurious fall incidents for the community dwelling elderly, a new dataframe is created where the row with the most
417.     # severe fracture is saved and the rest of the fractures (on the same day with the same patientnumber) are deleted.
418.
419.     # Create a copy of the original dataframe.
420.     DF_Injurious_Falls = Elderly_ERvisits_Relevant_Diagnoses
421.
422.     # Sort first on Cost then on severity.
423.     DF_Injurious_Falls = DF_Injurious_Falls.sort_values(['Classification','Cost_DOT_NZA'], ascending=[False, False])
424.
425.     # Drop the duplicates.
426.     DF_Injurious_Falls = DF_Injurious_Falls.drop_duplicates(subset = ['Startdate_DOT','Patient_Number'], keep='first')
427.
428.     # This new dataframe will be used to analyse the severity of the fractures and the number of injurious fall incidents. As you
429.     # can see below, the total number of rows is (~1000) lower than the other (cleaned) dataset containing all DOTs.
430.
431.     print(DF_Injurious_Falls.shape)
432.     print(Cleaned_ER_DOTS.shape)
433.
434.     ## Preparing the population dataset
435.
436.     # Load file with the population per (4 digit) zip codes per age category (per 5 years) and seperated in male and female. The
437.     # data is available for the last 5 years (Central bureau of Statistics, 2017).
438.
439.     Pop_PC4_Age_Sex_2014 = pd.read_csv('Datasets_csv/190325_BevolkingPerPostcode_1januari2014.csv',
440.                                         sep=',',
441.                                         encoding='ISO-8859-1')
442.
443.     Pop_PC4_Age_Sex_2015 = pd.read_csv('Datasets_csv/190325_BevolkingPerPostcode_1januari2015.csv',
444.                                         sep=',',
445.                                         encoding='ISO-8859-1')
446.
447.     Pop_PC4_Age_Sex_2016 = pd.read_csv('Datasets_csv/190325_BevolkingPerPostcode_1januari2016.csv',
448.                                         sep=',',
449.                                         encoding='ISO-8859-1')
450.
451.     Pop_PC4_Age_Sex_2017 = pd.read_csv('Datasets_csv/190325_BevolkingPerPostcode_1januari2017.csv',
452.                                         sep=',',

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453.                                         encoding='ISO-8859-1')
454.
455.     Pop_PC4_Age_Sex_2018 = pd.read_csv('Datasets_csv/190325_BevolkingPerPostcode_1januari2018.csv',
456.                                         sep=',',
457.                                         encoding='ISO-8859-1')
458.
459.     # Add column with year
460.     Pop_PC4_Age_Sex_2018['Year'] = 2018
461.     Pop_PC4_Age_Sex_2017['Year'] = 2017
462.     Pop_PC4_Age_Sex_2016['Year'] = 2016
463.     Pop_PC4_Age_Sex_2015['Year'] = 2015
464.     Pop_PC4_Age_Sex_2014['Year'] = 2014
465.
466.     # Create new columns for new categorizations: total 65+, 65-75, 75-
467.     # and 85+. An assumption is that the distribution between
468.     # men and women in the control-group is equal to the intervention-group.
469.
470.     # For 2014. Keep only the PC4 (zip code 4-digits) and the new categorizations.
471.     Pop_PC4_Age_Sex_2014['Total_65plus'] = Pop_PC4_Age_Sex_2014['65 tot 70 jaar VenM 2014'] +\
472.                                         Pop_PC4_Age_Sex_2014['70 tot 75 jaar VenM 2014'] +\
473.                                         Pop_PC4_Age_Sex_2014['75 tot 80 jaar VenM 2014'] +\
474.                                         Pop_PC4_Age_Sex_2014['80 tot 85 jaar VenM 2014'] +\
475.                                         Pop_PC4_Age_Sex_2014['85 tot 90 jaar VenM 2014'] +\
476.                                         Pop_PC4_Age_Sex_2014['90 tot 95 jaar VenM 2014'] +\
477.                                         Pop_PC4_Age_Sex_2014['95 jaar of ouder VenM 2014']
478.
479.     Pop_PC4_Age_Sex_2014['65-75'] = Pop_PC4_Age_Sex_2014['65 tot 70 jaar VenM 2014'] +\
480.                                         Pop_PC4_Age_Sex_2014['70 tot 75 jaar VenM 2014']
481.
482.     Pop_PC4_Age_Sex_2014['75-85'] = Pop_PC4_Age_Sex_2014['75 tot 80 jaar VenM 2014'] +\
483.                                         Pop_PC4_Age_Sex_2014['80 tot 85 jaar VenM 2014']
484.
485.     Pop_PC4_Age_Sex_2014['85+'] = Pop_PC4_Age_Sex_2014['85 tot 90 jaar VenM 2014'] +\
486.                                         Pop_PC4_Age_Sex_2014['90 tot 95 jaar VenM 2014'] +\
487.                                         Pop_PC4_Age_Sex_2014['95 jaar of ouder VenM 2014']
488.
489.     Pop_Categorized_2014 = Pop_PC4_Age_Sex_2014[['PC4', 'Year', '65-75', '75-85', '85+', \
490.                                         'Total_65plus']]
491.
492.     # For 2015. Keep only the PC4 (zip code 4-digits) and the new categorizations.
493.

```

```

494. Pop_PC4_Age_Sex_2015['Total_65plus'] = Pop_PC4_Age_Sex_2015['65 tot 70 jaar VenM 2015'] +\
495.                                         Pop_PC4_Age_Sex_2015['70 tot 75 jaar VenM 2015'] +\
496.                                         Pop_PC4_Age_Sex_2015['75 tot 80 jaar VenM 2015'] +\
497.                                         Pop_PC4_Age_Sex_2015['80 tot 85 jaar VenM 2015'] +\
498.                                         Pop_PC4_Age_Sex_2015['85 tot 90 jaar VenM 2015'] +\
499.                                         Pop_PC4_Age_Sex_2015['90 tot 95 jaar VenM 2015'] +\
500.                                         Pop_PC4_Age_Sex_2015['95 jaar of ouder VenM 2015']
501.
502. Pop_PC4_Age_Sex_2015['65-75'] = Pop_PC4_Age_Sex_2015['65 tot 70 jaar VenM 2015'] +\
503.                                         Pop_PC4_Age_Sex_2015['70 tot 75 jaar VenM 2015']
504.
505. Pop_PC4_Age_Sex_2015['75-85'] = Pop_PC4_Age_Sex_2015['75 tot 80 jaar VenM 2015'] +\
506.                                         Pop_PC4_Age_Sex_2015['80 tot 85 jaar VenM 2015']
507.
508. Pop_PC4_Age_Sex_2015['85+'] = Pop_PC4_Age_Sex_2015['85 tot 90 jaar VenM 2015'] +\
509.                                         Pop_PC4_Age_Sex_2015['90 tot 95 jaar VenM 2015'] +\
510.                                         Pop_PC4_Age_Sex_2015['95 jaar of ouder VenM 2015']
511.
512. Pop_Categorized_2015 = Pop_PC4_Age_Sex_2015[['PC4', 'Year', '65-75', '75-85', '85+',\
513.                                         'Total_65plus']]
514.
515. # For 2016. Keep only the PC4 (zip code 4-digits) and the new categorizations.
516.
517. Pop_PC4_Age_Sex_2016['Total_65plus'] = Pop_PC4_Age_Sex_2016['65 tot 70 jaar VenM 2016'] +\
518.                                         Pop_PC4_Age_Sex_2016['70 tot 75 jaar VenM 2016'] +\
519.                                         Pop_PC4_Age_Sex_2016['75 tot 80 jaar VenM 2016'] +\
520.                                         Pop_PC4_Age_Sex_2016['80 tot 85 jaar VenM 2016'] +\
521.                                         Pop_PC4_Age_Sex_2016['85 tot 90 jaar VenM 2016'] +\
522.                                         Pop_PC4_Age_Sex_2016['90 tot 95 jaar VenM 2016'] +\
523.                                         Pop_PC4_Age_Sex_2016['95 jaar of ouder VenM 2016']
524.
525. Pop_PC4_Age_Sex_2016['65-75'] = Pop_PC4_Age_Sex_2016['65 tot 70 jaar VenM 2016'] +\
526.                                         Pop_PC4_Age_Sex_2016['70 tot 75 jaar VenM 2016']
527.
528. Pop_PC4_Age_Sex_2016['75-85'] = Pop_PC4_Age_Sex_2016['75 tot 80 jaar VenM 2016'] +\
529.                                         Pop_PC4_Age_Sex_2016['80 tot 85 jaar VenM 2016']
530.
531. Pop_PC4_Age_Sex_2016['85+'] = Pop_PC4_Age_Sex_2016['85 tot 90 jaar VenM 2016'] +\
532.                                         Pop_PC4_Age_Sex_2016['90 tot 95 jaar VenM 2016'] +\
533.                                         Pop_PC4_Age_Sex_2016['95 jaar of ouder VenM 2016']
534.
535. Pop_Categorized_2016 = Pop_PC4_Age_Sex_2016[['PC4', 'Year', '65-75', '75-85', '85+',
```

```

536.                                         'Total_65plus']]
```

537.

538. # For 2017. Keep only the PC4 (zip code 4-digits) and the new categorizations.

539.

```

540. Pop_PC4_Age_Sex_2017['Total_65plus'] = Pop_PC4_Age_Sex_2017['65 tot 70 jaar VenM 2017'] +\
541.                                         Pop_PC4_Age_Sex_2017['70 tot 75 jaar VenM 2017'] +\
542.                                         Pop_PC4_Age_Sex_2017['75 tot 80 jaar VenM 2017'] +\
543.                                         Pop_PC4_Age_Sex_2017['80 tot 85 jaar VenM 2017'] +\
544.                                         Pop_PC4_Age_Sex_2017['85 tot 90 jaar VenM 2017'] +\
545.                                         Pop_PC4_Age_Sex_2017['90 tot 95 jaar VenM 2017'] +\
546.                                         Pop_PC4_Age_Sex_2017['95 jaar of ouder VenM 2017']
```

547.

```

548. Pop_PC4_Age_Sex_2017['65-75'] = Pop_PC4_Age_Sex_2017['65 tot 70 jaar VenM 2017'] +\
549.                                         Pop_PC4_Age_Sex_2017['70 tot 75 jaar VenM 2017']
```

550.

```

551. Pop_PC4_Age_Sex_2017['75-85'] = Pop_PC4_Age_Sex_2017['75 tot 80 jaar VenM 2017'] +\
552.                                         Pop_PC4_Age_Sex_2017['80 tot 85 jaar VenM 2017']
```

553.

```

554. Pop_PC4_Age_Sex_2017['85+'] = Pop_PC4_Age_Sex_2017['85 tot 90 jaar VenM 2017'] +\
555.                                         Pop_PC4_Age_Sex_2017['90 tot 95 jaar VenM 2017'] +\
556.                                         Pop_PC4_Age_Sex_2017['95 jaar of ouder VenM 2017']
```

557.

```

558. Pop_Categorized_2017 = Pop_PC4_Age_Sex_2017[['PC4', 'Year', '65-75', '75-85', '85+',\
559.                                         'Total_65plus']]
```

560.

561. # For 2018. Keep only the PC4 (zip code 4-digits) and the new categorizations.

562.

```

563. Pop_PC4_Age_Sex_2018['Total_65plus'] = Pop_PC4_Age_Sex_2018['65 tot 70 jaar VenM 2018'] +\
564.                                         Pop_PC4_Age_Sex_2018['70 tot 75 jaar VenM 2018'] +\
565.                                         Pop_PC4_Age_Sex_2018['75 tot 80 jaar VenM 2018'] +\
566.                                         Pop_PC4_Age_Sex_2018['80 tot 85 jaar VenM 2018'] +\
567.                                         Pop_PC4_Age_Sex_2018['85 tot 90 jaar VenM 2018'] +\
568.                                         Pop_PC4_Age_Sex_2018['90 tot 95 jaar VenM 2018'] +\
569.                                         Pop_PC4_Age_Sex_2018['95 jaar of ouder VenM 2018']
```

570.

```

571. Pop_PC4_Age_Sex_2018['65-75'] = Pop_PC4_Age_Sex_2018['65 tot 70 jaar VenM 2018'] +\
572.                                         Pop_PC4_Age_Sex_2018['70 tot 75 jaar VenM 2018']
```

573.

```

574. Pop_PC4_Age_Sex_2018['75-85'] = Pop_PC4_Age_Sex_2018['75 tot 80 jaar VenM 2018'] +\
575.                                         Pop_PC4_Age_Sex_2018['80 tot 85 jaar VenM 2018']
```

576.

```

577. Pop_PC4_Age_Sex_2018['85+'] = Pop_PC4_Age_Sex_2018['85 tot 90 jaar VenM 2018'] +\
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```

578.                                         Pop_PC4_Age_Sex_2018['90 tot 95 jaar VenM 2018'] +\
579.                                         Pop_PC4_Age_Sex_2018['95 jaar of ouder VenM 2018']
580.
581.     Pop_Categorized_2018 = Pop_PC4_Age_Sex_2018[['PC4','Year','65-75','75-85','85+',\
582.                                                 'Total_65plus']]
583.
584.     # Combine datasets into one dataframe. Note that this dataframe contains all elderly, while the focus of this analysis
585.     # is on the community-dwelling elderly.
586.
587.     Pop_Combined_All = pd.concat([Pop_Categorized_2014, Pop_Categorized_2015,Pop_Categorized_2016,Pop_Categorized_2017,
588.                                     Pop_Categorized_2018])
589.
590.     # Rename column indicating that this data contains both community-dwelling- and nursing home elderly.
591.
592.     Pop_Combined_All.columns = ['PC4',
593.                                 'Year',
594.                                 '65-75All',
595.                                 '75-85All',
596.                                 '85+All',
597.                                 'Total65Plus All']
598.
599.     # However, a dataframe has to be created containing the population per zip code with only the community-dwelling elderly.
600.
601.
602.     # Load file containing the data (Central Bureau of Statistics, 2018).
603.
604.     Perc_comm_dwelling_per_age_group = pd.read_csv('Datasets_csv/190628_Percentages_community_dwelling_per_age_group.csv',
605.                                                     sep=',',
606.                                                     encoding='ISO-8859-1')
607.
608.     # Copy the Pop_Combined_All dataset.
609.
610.     Pop_Combined = Pop_Combined_All.copy()
611.
612.     # Add three columns with the percentage of community-dwelling elderly.
613.
614.     Pop_Combined.loc[Pop_Combined['Year'] == 2014,'Percentage nursing 65-75'] =\
615.         float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group['AgeGroup'] == '65-75','2014'])
616.     Pop_Combined.loc[Pop_Combined['Year'] == 2015,'Percentage nursing 65-75'] =\
617.         float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group['AgeGroup'] == '65-75','2015'])
618.     Pop_Combined.loc[Pop_Combined['Year'] == 2016,'Percentage nursing 65-75'] =\
619.         float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group['AgeGroup'] == '65-75','2016'])

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```

620. Pop_Combined.loc[Pop_Combined['Year'] == 2017, 'Percentage nursing 65-75'] =\
621.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '65-75','2017'])
622. Pop_Combined.loc[Pop_Combined['Year'] == 2018, 'Percentage nursing 65-75'] =\
623.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '65-75','2018'])
624.
625. Pop_Combined.loc[Pop_Combined['Year'] == 2014, 'Percentage nursing 75-85'] =\
626.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '75-85','2014'])
627. Pop_Combined.loc[Pop_Combined['Year'] == 2015, 'Percentage nursing 75-85'] =\
628.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '75-85','2015'])
629. Pop_Combined.loc[Pop_Combined['Year'] == 2016, 'Percentage nursing 75-85'] =\
630.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '75-85','2016'])
631. Pop_Combined.loc[Pop_Combined['Year'] == 2017, 'Percentage nursing 75-85'] =\
632.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '75-85','2017'])
633. Pop_Combined.loc[Pop_Combined['Year'] == 2018, 'Percentage nursing 75-85'] =\
634.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '75-85','2018'])
635.
636. Pop_Combined.loc[Pop_Combined['Year'] == 2014, 'Percentage nursing 85+'] =\
637.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '85+','2014'])
638. Pop_Combined.loc[Pop_Combined['Year'] == 2015, 'Percentage nursing 85+'] =\
639.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '85+','2015'])
640. Pop_Combined.loc[Pop_Combined['Year'] == 2016, 'Percentage nursing 85+'] =\
641.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '85+','2016'])
642. Pop_Combined.loc[Pop_Combined['Year'] == 2017, 'Percentage nursing 85+'] =\
643.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '85+','2017'])
644. Pop_Combined.loc[Pop_Combined['Year'] == 2018, 'Percentage nursing 85+'] =\
645.     float(Perc_comm_dwelling_per_age_group.loc[Perc_comm_dwelling_per_age_group[ 'AgeGroup'] == '85+','2018'])
646.
647. # Create three columns with only the community dwelling elderly. These three columns will be used to conduct the analysis in
648. # the following sections.
649.
650. Pop_Combined['65-75'] = round(Pop_Combined['65-75All'] * Pop_Combined['Percentage nursing 65-75'],0)
651. Pop_Combined['75-85'] = round(Pop_Combined['75-85All'] * Pop_Combined['Percentage nursing 75-85'],0)
652. Pop_Combined['85+'] = round(Pop_Combined['85+All'] * Pop_Combined['Percentage nursing 85+'],0)
653.
654.
655. # Determining the treatment- and control group
656.
657. # As sufficient data has been collected, a control- and intervention group can be defined which will be included in the dataset
658. # to analyze the effect of fall prevention programs using the DID method (see chapter 4 of report).
659.
```

```

660.      # To prevent bias in the data, the SES-
661.      # scores of the control group should be close to the SES score of the treatment group (see
662.      # chapter 5 of the report). In the section below, the socioeconomic status of several areas in and around Dordrecht (potential
663.      # control groups) are compared to the intervention group. If the difference in SES score between the intervention areas and a
664.      # (potential) control group area is less than one, the elderly population in that area will be part of the control group.
665.      # The following control areas will be assessed: Dordrecht-
666.      # West (zip code 3311, 3312, 3314), Papendrecht (zip code 3351, 3352,
667.      # 3353, 3354, 3355), Zwijndrecht (zip code 3331, 3332, 3333, 3334, 3335), Henrik-Ido-
668.      # Ambacht (zip code 3341, 3342, 3343, 3344),
669.      # and Sliedrecht (zip code 3361 and 3362).
670.
671.      # The fall prevention programs have been implemented in the east of Dordrecht in the following neighborhoods: Sterrenburg (zip
672.      # code 3318 and 3328), Stadspolders (zip code 3315), Crabbehof (zip code 3317) and Dubbeldam (zip code 3319). These areas are
673.      # the treatment (or intervention) group (Drechtmax, 2017).
674.      SES_scores_regions = pd.read_csv('Datasets_csv/190328_SES_Scores_Regions.csv',
675.                                          sep=';',
676.                                          encoding='ISO-8859-1')
677.
678.      # Select only the relevant columns and rename these columns.
679.
680.      SES_scores_regions = SES_scores_regions[['pcnr','statusscore17']]
681.      SES_scores_regions.columns = ['PC4','SES_Score_2017']
682.
683.      # Select only the relevant zip codes of the regions discussed above. Large areas with a small population such as
684.      # 'Dordtse Biesbosch' (zip code 3329 and 3313) and industrial/agricultural areas (zip code 3316, 3356, 3363, 3364, 3336) are
685.      # excluded from the dataset.
686.
687.      SES_scores_regions = SES_scores_regions[
688.          ((SES_scores_regions['PC4'] > 3310) & (SES_scores_regions['PC4'] < 3313)) | # Dordrecht-West
689.          ((SES_scores_regions['PC4'] > 3313) & (SES_scores_regions['PC4'] < 3315)) | # Dordrecht-West
690.          ((SES_scores_regions['PC4'] > 3314) & (SES_scores_regions['PC4'] < 3316)) | # Dordrecht-Oost
691.          ((SES_scores_regions['PC4'] > 3316) & (SES_scores_regions['PC4'] < 3320)) | # Dordrecht-Oost
692.          ((SES_scores_regions['PC4'] > 3327) & (SES_scores_regions['PC4'] < 3329)) | # Dordrecht-Oost
693.          ((SES_scores_regions['PC4'] > 3360) & (SES_scores_regions['PC4'] < 3363)) | # Sliedrecht
694.          ((SES_scores_regions['PC4'] > 3350) & (SES_scores_regions['PC4'] < 3356)) | # Papendrecht
695.          ((SES_scores_regions['PC4'] > 3340) & (SES_scores_regions['PC4'] < 3345)) | # Henrik-Ido-Ambacht
696.          ((SES_scores_regions['PC4'] > 3330) & (SES_scores_regions['PC4'] < 3336)) ] # Zwijndrecht

```

```

697.
698.     # Add a column indicating the region.
699.
700.     def assign_region(PC4):
701.         if ((PC4 > 3310) & (PC4 < 3313)):    # Neighborhoods: Centrum, Indische Buurt
702.             return 'Dordrecht-West'
703.         elif ((PC4 > 3313) & (PC4 < 3315)):   # Krispijn
704.             return 'Dordrecht-West'
705.         elif ((PC4 > 3314) & (PC4 < 3316)):   # Stadspolders
706.             return 'Dordrecht-Oost'
707.         elif ((PC4 > 3316) & (PC4 < 3320)):   # Sterrenburg (1), Dubbeldam, Crabbehof
708.             return 'Dordrecht-Oost'
709.         elif ((PC4 > 3327) & (PC4 < 3329)):   # Sterrenburg (2nd zip code)
710.             return 'Dordrecht-Oost'
711.         elif ((PC4 > 3360) & (PC4 < 3363)):   # Sliedrecht
712.             return 'Sliedrecht'
713.         elif ((PC4 > 3350) & (PC4 < 3356)):   # Papendrecht
714.             return 'Papendrecht'
715.         elif ((PC4 > 3340) & (PC4 < 3345)):   # Henrik-Ido-Ambacht
716.             return 'Henrik-Ido-Ambacht'
717.         elif ((PC4 > 3330) & (PC4 < 3336)):   # Zwijndrecht
718.             return 'Zwijndrecht'
719.
720.     SES_scores_regions['Region'] = SES_scores_regions.PC4.apply(assign_region)
721.
722.     # Convert SES scores to float.
723.
724.     SES_scores_regions['SES_Score_2017'] = SES_scores_regions['SES_Score_2017'].str.replace(',', '.')
725.     SES_scores_regions['SES Score 2017'] = SES_scores_regions['SES Score 2017'].astype(float)
726.
727.     # Compute the mean SES score per region.
728.
729.     Average_Score_per_Region = SES_scores_regions.groupby('Region').mean().reset_index()
730.     del Average_Score_per_Region['PC4']
731.     Average_Score_per_Region['SES_Score_2017'] = Average_Score_per_Region['SES_Score_2017'].round(2)
732.
733.     # Create a table with the results. On basis of this table, the following control areas have been chosen: Dordrecht-West,
734.     # Sliedrecht and Zwijndrecht. The intervention area is Dordrecht-Oost.
735.
736.     import six
737.     def Make_Pretty_Table(data, col_width=3.0, row_height=0.625, font_size=14,
738.                           header_color='#8EAADB', row_colors=['#f1f1f2', 'w'], edge_color='w',

```

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739.                 bbox=[0, 0, 1, 1], header_columns=0,
740.                 ax=None, **kwargs):
741.             if ax is None:
742.                 size = (np.array(data.shape[::-1]) + np.array([0, 1])) * np.array([col_width, row_height])
743.                 fig, ax = plt.subplots(figsize=size)
744.                 ax.axis('off')
745.
746.             mpl_table = ax.table(cellText=data.values, bbox=bbox, colLabels=data.columns, **kwargs)
747.
748.             mpl_table.auto_set_font_size(False)
749.             mpl_table.set_fontsize(font_size)
750.
751.             for k, cell in six.iteritems(mpl_table._cells):
752.                 cell.set_edgecolor(edge_color)
753.                 if k[0] == 0 or k[1] < header_columns:
754.                     cell.set_text_props(weight='bold', color='w')
755.                     cell.set_facecolor(header_color)
756.                 else:
757.                     cell.set_facecolor(row_colors[k[0] % len(row_colors)])
758.             return ax
759.
760. img = Make_Pretty_Table(Average_Score_per_Region, header_columns=0, col_width=3.0)
761.
762. # Data preparation for analysis
763.
764. # In this section, the population-dataset is reduced by selecting only the relevant zip-codes based on the previous analysis.
765.
766. Pop_Combined['PC4'] = Pop_Combined['PC4'].astype(str)
767. Pop_Combined = Pop_Combined[Pop_Combined['PC4'].str.startswith('33')]
768. Pop_Combined['PC4'] = Pop_Combined['PC4'].astype(float)
769. Pop_Combined['PC4'] = Pop_Combined['PC4'].astype(int)
770.
771. Pop_Combined_Dord = Pop_Combined[
772.             ((Pop_Combined['PC4'] > 3310) & (Pop_Combined['PC4'] < 3313)) | # Dordrecht-West
773.             ((Pop_Combined['PC4'] > 3313) & (Pop_Combined['PC4'] < 3315)) | # Dordrecht-West
774.             ((Pop_Combined['PC4'] > 3314) & (Pop_Combined['PC4'] < 3316)) | # Dordrecht-Oost
775.             ((Pop_Combined['PC4'] > 3316) & (Pop_Combined['PC4'] < 3320)) | # Dordrecht-Oost
776.             ((Pop_Combined['PC4'] > 3327) & (Pop_Combined['PC4'] < 3329)) | # Dordrecht-Oost
777.             ((Pop_Combined['PC4'] > 3360) & (Pop_Combined['PC4'] < 3363)) | # Sliedrecht
778.             ((Pop_Combined['PC4'] > 3330) & (Pop_Combined['PC4'] < 3336)) ] # Zwijndrecht
779.
780. # Melt dataframe in order to create a simular format as the main dataframe.

```

```

781.
782. Pop_Combined_Dord = Pop_Combined_Dord[['PC4', 'Year', '65-75', '75-85', '85+']]
783.
784. Pop_Combined_Dord = pd.melt(Pop_Combined_Dord, id_vars=['PC4', 'Year'], var_name="Age_Group", value_name="Population")
785.
786. # Check shape: first number is rows, second number is columns.
787.
788. Pop_Combined_Dord.shape
789.
790. # Mutate the main dataframe the same way as the population-dataset.
791.
792. Cleaned_ER_DOTs['PC4'] = Cleaned_ER_DOTs['PC4'].astype(int)
793.
794. ER_DOTs_Case = Cleaned_ER_DOTs[
795.             ((Cleaned_ER_DOTs['PC4'] > 3310) & (Cleaned_ER_DOTs['PC4'] < 3313)) | # Dordrecht-West
796.             ((Cleaned_ER_DOTs['PC4'] > 3313) & (Cleaned_ER_DOTs['PC4'] < 3315)) | # Dordrecht-West
797.             ((Cleaned_ER_DOTs['PC4'] > 3314) & (Cleaned_ER_DOTs['PC4'] < 3316)) | # Dordrecht-Oost
798.             ((Cleaned_ER_DOTs['PC4'] > 3316) & (Cleaned_ER_DOTs['PC4'] < 3320)) | # Dordrecht-Oost
799.             ((Cleaned_ER_DOTs['PC4'] > 3327) & (Cleaned_ER_DOTs['PC4'] < 3329)) | # Dordrecht-Oost
800.             ((Cleaned_ER_DOTs['PC4'] > 3360) & (Cleaned_ER_DOTs['PC4'] < 3363)) | # Sliedrecht
801.             ((Cleaned_ER_DOTs['PC4'] > 3330) & (Cleaned_ER_DOTs['PC4'] < 3336)) ] # Zwijndrecht
802.
803. # Drop the rows in with DOTs created in January, February 2013 and December 2018.
804.
805. ER_DOTs_Case = ER_DOTs_Case.drop(ER_DOTs_Case[
806.                                         ER_DOTs_Case.Time_Period == 'Unreliable_data'].index)
807.
808. # Drop the rows which are not included in the analysis.
809.
810. ER_DOTs_Case = ER_DOTs_Case.drop(ER_DOTs_Case[
811.                                         ER_DOTs_Case.Time_Period == 'NOT_COMPLETE_PERIOD_Winter2014'].index)
812.
813. ER_DOTs_Case = ER_DOTs_Case.drop(ER_DOTs_Case[
814.                                         ER_DOTs_Case.Analysis_Year == 'NOT_COMPLETE_PERIOD_Winter2014'].index)
815.
816. # Add a column indicating the district based on the zip code 4-digits.
817.
818. ER_DOTs_Case['PC4'] = ER_DOTs_Case['PC4'].astype(str)
819.
820. ER_DOTs_Case['District'] = np.where(ER_DOTs_Case['PC4'].
821.                                         str.startswith('3311'), 'Centrum Dordrecht',
822.                                         np.where(ER_DOTs_Case['PC4'].

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```

823.             str.startswith('3312'), 'Indisch Buurt en LV Valk',
824.             np.where(ER_DOTs_Case['PC4']).
825.             str.startswith('3314'), 'Krispijn',
826.             np.where(ER_DOTs_Case['PC4']).
827.             str.startswith('3315'), 'Stadspolder',
828.             np.where(ER_DOTs_Case['PC4']).
829.             str.startswith('3317'), 'Crabbehof, Wielwijk, Hout',
830.             np.where(ER_DOTs_Case['PC4']).
831.             str.startswith('3318'), 'Sterrenburg 1',
832.             np.where(ER_DOTs_Case['PC4']).
833.             str.startswith('3319'), 'Dubbeldam',
834.             np.where(ER_DOTs_Case['PC4']).
835.             str.startswith('3328'), 'Sterrenburg 2',
836.             np.where(ER_DOTs_Case['PC4']).
837.             str.startswith('3331'), 'Zwijndrecht 1',
838.             np.where(ER_DOTs_Case['PC4']).
839.             str.startswith('3332'), 'Zwijndrecht 2',
840.             np.where(ER_DOTs_Case['PC4']).
841.             str.startswith('3333'), 'Zwijndrecht 3',
842.             np.where(ER_DOTs_Case['PC4']).
843.             str.startswith('3334'), 'Zwijndrecht 4',
844.             np.where(ER_DOTs_Case['PC4']).
845.             str.startswith('3335'), 'Zwijndrecht 5',
846.             np.where(ER_DOTs_Case['PC4']).
847.             str.startswith('3361'), 'Sliedrecht 1',
848.             np.where(ER_DOTs_Case['PC4']).
849.             str.startswith('3362'), 'Sliedrecht 2', 0)))))))))))))))))

850.

851. # Add a column indicating whether the zip code is part of the control group, the intervention group or no group .
852.

853. ER_DOTs_Case['Group'] = np.where(ER_DOTs_Case['PC4'].
854.             str.startswith('3311'), 'Control group',
855.             np.where(ER_DOTs_Case['PC4'].
856.             str.startswith('3312'), 'Control group',
857.             np.where(ER_DOTs_Case['PC4'].
858.             str.startswith('3314'), 'Control group',
859.             np.where(ER_DOTs_Case['PC4'].
860.             str.startswith('3315'), 'Intervention group',
861.             np.where(ER_DOTs_Case['PC4'].
862.             str.startswith('3317'), 'Intervention group',
863.             np.where(ER_DOTs_Case['PC4'].
864.             str.startswith('3318'), 'Intervention group',

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865.             np.where(ER_DOTS_Case['PC4'].
866.                         str.startswith('3319'), 'Intervention group',
867.                         np.where(ER_DOTS_Case['PC4'].
868.                         str.startswith('3328'), 'Intervention group',
869.                         np.where(ER_DOTS_Case['PC4'].
870.                         str.startswith('3331'), 'Control group',
871.                         np.where(ER_DOTS_Case['PC4'].
872.                         str.startswith('3332'), 'Control group',
873.                         np.where(ER_DOTS_Case['PC4'].
874.                         str.startswith('3333'), 'Control group',
875.                         np.where(ER_DOTS_Case['PC4'].
876.                         str.startswith('3334'), 'Control group',
877.                         np.where(ER_DOTS_Case['PC4'].
878.                         str.startswith('3335'), 'Control group',
879.                         np.where(ER_DOTS_Case['PC4'].
880.                         str.startswith('3361'), 'Control group',
881.                         np.where(ER_DOTS_Case['PC4'].
882.                         str.startswith('3362'), 'Control group', 0)))))))))))))))
883.
884. ER_DOTS_Case.shape
885.
886. # Add the group type (intervention, no group, control group) to the dataframe with the population per area.
887.
888. DF_Dord_Group = pd.DataFrame(ER_DOTS_Case[['PC4','Group']])
889.
890. DF_Dord_Group['PC4'] = DF_Dord_Group['PC4'].astype(int)
891. Pop_Combined_Dord['PC4'] = Pop_Combined_Dord['PC4'].astype(int)
892.
893. DF_Dord_Group= DF_Dord_Group.drop_duplicates(subset='PC4', keep="first")
894.
895. Pop_Combined_Dord = pd.merge(Pop_Combined_Dord,DF_Dord_Group,how='left',on='PC4')
896.
897. Pop_Combined_Dord.shape
898.
899. # Drop the rows with year 2018 in the population dataset (the population of 2017 is used for analysis year 2017-2018).
900.
901. Pop_Combined_Dord = Pop_Combined_Dord.drop(Pop_Combined_Dord[
902.                                         Pop_Combined_Dord.Year == 2018].index)
903.
904. Pop_Combined_Dord.shape
905.
906. # Check if there are any missing values in the population dataframe.

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```

907.     print(Pop_Combined_Dord.isnull().values.any())
908.
909.
910. # The DataFrame 'ER_DOTs_Case' contains all the fall related DOTs of elderly and can be used to determine the effect of the
911. # fall prevention programs on the hospital expenditures. However, another dataframe needs to be created to analyse the number
912. # of injurious fall incidents and the severity of these falls, because it is possible that an older adult has multiple
913. # fractures after a fall. This DataFrame needs to contain data with only the most severe fracture per fall incident. The rest
914. # of the fractures (on the same day with the same patientnumber) must be deleted.
915. # The DataFrame 'DF_Injurious_Falls' contains data with only the most severe fracture per fall incident. To get the proper data
916. # for this case, it is possible to delete the DOTs (rows) in the DataFrame 'ER_DOTs_Case' based on the unique DOT-ID in the
917. # DataFrame 'DF_Injurious_Falls'.
918.
919. DF_Falls_Case = ER_DOTs_Case[
920.             ER_DOTs_Case['ID'].isin(DF_Injurious_Falls['ID'].unique())]
921.
922.
923. # Add a column indicating the region in both DataFrames.
924.
925. ER_DOTs_Case['PC4'] = ER_DOTs_Case['PC4'].astype(int)
926. DF_Falls_Case['PC4'] = DF_Falls_Case['PC4'].astype(int)
927. ER_DOTs_Case['Region'] = ER_DOTs_Case.PC4.apply(assign_region)
928. DF_Falls_Case['Region'] = DF_Falls_Case.PC4.apply(assign_region)
929.
930. # This new dataframe will be used to analyse the severity of the fractures and the number of injurious fall incidents. As you
931. # can see below, the total number of rows is (~500) lower than the other case-dataset.
932.
933. print(DF_Falls_Case.shape)
934. print(ER_DOTs_Case.shape)
935.
936. # Calculation and visualization of results
937.
938. ## Analysis to determine the effect of the programs on the number of fall incidents
939.
940. ### Visualizing the average yearly hospital expenditures per elderly per age group
941.
942. # Create a pivot table containing an overview of the costs of the DOTs related to fall incidents.
943.
944. Pivot_Costs_Overview = ER_DOTs_Case[ER_DOTs_Case.Analysis_Year == "2017-2018"].pivot_table(columns='Age_Group',
945.                                         index='Classification',

```

```

946.                                         values='Final_DOT_Cost',
947.                                         aggfunc=np.sum)
948.
949.     # Prepare the data for visualization.
950.
951.     Severity_1_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[0:3]
952.     Severity_2_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[3:6]
953.     Severity_3_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[6:9]
954.     Severity_4_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[9:12]
955.     Severity_5_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[12:15]
956.     Severity_6_All_agegroups = Pivot_Costs_Overview.values.flatten().tolist()[15:18]
957.
958.     # Plot stacked barchart to visualize the cost of the falls per age group.
959.
960.     # Import plotly for nice styling of the plots.
961.
962.     import plotly.plotly as py
963.     import plotly.graph_objs as go
964.     import plotly.io as pio
965.     from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
966.     init_notebook_mode(connected=True)
967.
968.     Severity1 = go.Bar(
969.         x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],
970.         y=Severity_1_All_agegroups,
971.         marker=dict(
972.             color=['RGB(166, 217, 106)', 'RGB(166, 217, 106)',
973.                   'RGB(166, 217, 106)'],
974. #             width = [0.5, 0.5, 0.5],
975.             name='Severity 1'
976.         )
977.     Severity2 = go.Bar(
978.         x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],
979.         y=Severity_2_All_agegroups,
980.         marker=dict(
981.             color=['RGB(217, 239, 139)', 'RGB(217, 239, 139)',
982.                   'RGB(217, 239, 139)'],
983. #             width = [0.5, 0.5, 0.5],
984.             name='Severity 2'
985.         )
986.     Severity3 = go.Bar(
987.         x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],

```

```

988.         y=Severity_3_All_agegroups,
989.         marker=dict(
990.             color=['RGB(254, 224, 139)', 'RGB(254, 224, 139)',
991.                   'RGB(254, 224, 139)']),
992.             #     width = [0.5, 0.5, 0.5],
993.             name='Severity 3'
994.         )
995. Severity4 = go.Bar(
996.     x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],
997.     y=Severity_4_All_agegroups,
998.     marker=dict(
999.         color=['RGB(253, 174, 97)', 'RGB(253, 174, 97)',
1000.                 'RGB(253, 174, 97)']),
1001.             #     width = [0.5, 0.5, 0.5],
1002.             name='Severity 4'
1003.         )
1004. Severity5 = go.Bar(
1005.     x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],
1006.     y=Severity_5_All_agegroups,
1007.     marker=dict(
1008.         color=['RGB(244, 109, 67)', 'RGB(244, 109, 67)',
1009.                 'RGB(244, 109, 67)']),
1010.             #     width = [0.5, 0.5, 0.5],
1011.             name='Severity 5'
1012.         )
1013. Severity6 = go.Bar(
1014.     x=['Age group 65-75', 'Age group 75-85', 'Age group 85+'],
1015.     y=Severity_6_All_agegroups,
1016.     marker=dict(
1017.         color=['RGB(215, 48, 39)', 'RGB(215, 48, 39)',
1018.                 'RGB(215, 48, 39)']),
1019.             #     width = [0.5, 0.5, 0.5],
1020.             name='Severity 6'
1021.         )
1022.
1023. data = [Severity1, Severity2, Severity3, Severity4, Severity5, Severity6]
1024. layout = go.Layout(
1025.     barmode='stack',
1026.     width=600,
1027.     height=500,
1028.     yaxis = dict(title = 'Total yearly costs of falls (€)'),
1029.     font=dict(family='Calibri', size=14,

```

```

1030.         color='rgb(67, 67, 67)'),
1031.     #     width = [0.8, 0.8, 0.8]
1032. )
1033.
1034. fig_overview = go.Figure(data=data, layout=layout)
1035. iplot(fig_overview, filename='stacked-bar')
1036.
1037. # pio.write_image(fig_overview, 'Total costs of falls All groups2.png')
1038. # fig_overview.savefig('Total costs of falls All groups.png', dpi=500, bbox_inches='tight')
1039.
1040. ### Testing Common Trend Assumption (CTA)
1041.
1042. ##### Plot the number of injurious falls per 100 elderly per group over time
1043.
1044. # Create a pivot table with the total number of injurious fall incidents per analysis-year and group, and exclude DOTs
1045. # created for elderly above age 85. This is because the fall prevention programs are designed for elderly between 65 and 85.
1046.
1047. Pivot_Falls_Age65_85 = DF_Falls_Case[DF_Falls_Case.Age_Group != "85+"].pivot_table(columns='Group', index='Analysis_Year',
1048.                                         values='Number_of_DOTs', aggfunc=np.sum, fill_value=0)
1049.
1050. # Create a pivot table with the population per group per year, and filter on age group 65-85.
1051.
1052. Popluation_CTA_65_85 = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1053.
1054. Pivot_Population_CTA_65_85 = Popluation_CTA_65_85[Popluation_CTA_65_85.Age_Group != "85+"].pivot_table(columns='Group',
1055.                                         index='Year',
1056.                                         values='Population',
1057.                                         aggfunc=np.sum, fill_value=0)
1058.
1059. # Replace the pivot table with values of (the number of injurious falls / the population)*100 to create the outcome variable:
1060. # Number of injurious falls per 100 elderly.
1061.
1062. Pivot_Falls_Age65_85[:] = (Pivot_Falls_Age65_85.values/Pivot_Population_CTA_65_85.values) * 100
1063.
1064. # Prepare data for visualization.
1065.
1066. Control_group65_85 = go.Scatter(
1067.     x = ['2014-2015','2015-2016','2016-2017','2017-2018'],
1068.     y = [(Pivot_Falls_Age65_85.values.flatten()).tolist()[0], (Pivot_Falls_Age65_85.values.flatten()).tolist()[2],
1069.           (Pivot_Falls_Age65_85.values.flatten()).tolist()[4], (Pivot_Falls_Age65_85.values.flatten()).tolist()[6]],
1070.     name = 'Control Group 65-85',
1071.     line = dict(

```

```

1072.         color = ('rgba(219, 64, 82, 0.7)'),
1073.         width = 3)
1074.     )
1075. Intervention_group65_85 = go.Scatter(
1076.     x = ['2014-2015', '2015-2016', '2016-2017', '2017-2018'],
1077.     y = [(Pivot_Falls_Age65_85.values.flatten()).tolist()[1], (Pivot_Falls_Age65_85.values.flatten()).tolist()[3],
1078.           (Pivot_Falls_Age65_85.values.flatten()).tolist()[5], (Pivot_Falls_Age65_85.values.flatten()).tolist()[7]],
1079.     name = 'Intervention Group 65-85',
1080.     line = dict(
1081.         color = ('RGB(142,170,219)'),
1082.         width = 3)
1083.     )
1084.
1085. data = [Control_group65_85, Intervention_group65_85]
1086.
1087. layout = go.Layout(
1088.     autosize=False,
1089.     width=1000,
1090.     height=500,
1091.     yaxis = dict(title = 'Fall incidents per 100 elderly',
1092.                   range = [0,6]),
1093.     font=dict(family='Calibri', size=14,
1094.               color='rgb(67, 67, 67)'))
1095.
1096. fig2 = go.Figure(data=data, layout=layout)
1097. iplot(fig2, filename='basic-line')
1098.
1099. # pio.write_image(fig2, 'CTA_Age65_8.png')
1100.
1101. # The control- and intervention group in both age groups show similar trends pre-intervention. The common trend assumption
1102. # holds true. The two lines show different behavior post-intervention (between year 2016-2017 and year
1103. # 2017-2018): it seems that the fall prevention programs have an effect on the number of injurious fall incidents per 100
1104. # elderly. With the DID regression model described in the section 'Running Weighted Least Squares (WLS) Difference-in-
1105. # Differences (DID) regression' the effect of the fall prevention programs for each age group will be estimated. However,
1106. # a test needs to be done to test the CTA. This will be done in the next section.
1107.
1108. ##### Test the CTA using the DID method in the pre-intervention period
1109.
1110. # The DID method (described in chapter 4 of the report) is used to determine whether the CTA holds. The DID method is used to
1111. # determine whether there is a difference in the trends between the groups in the pre-
    intervention years. Two analyses will be

```

```

1112.      # done: by checking the trend between year 2014-2015 and year 2015-2016, and year 2015-2016 and 2016-
1113.      # The CTA holds when
1114.      # the coefficient of the DID estimate is close to 0 and the p-value is high.
1115.      # In the next section, the difference in trends between year 2014-2015 and year 2015-2016 is determined.
1116.
1117.      # The statsmodels module is imported. This module is used to run the WLS regression.
1118.
1119.      import statsmodels.api as sm
1120.
1121.      CTA_test_1415_1516 = DF_Falls_Case
1122.
1123.      # A pivot table is created with the number of injurious falls per zip code per analysis year. Filter on age group 65-85.
1124.      # For this analysis, it is necessary to remove the data in year 2016-2017 and 2017-2018.
1125.
1126.      CTA_test_1415_1516 = CTA_test_1415_1516.drop(CTA_test_1415_1516[
1127.                                              CTA_test_1415_1516.Analysis_Year == '2017-2018'].index)
1128.
1129.      CTA_test_1415_1516 = CTA_test_1415_1516.drop(CTA_test_1415_1516[
1130.                                              CTA_test_1415_1516.Analysis_Year == '2016-2017'].index)
1131.
1132.      Pivot_CTA_test_1415_1516 = CTA_test_1415_1516[CTA_test_1415_1516.Age_Group != "85+"].pivot_table(
1133.                                              index=['Analysis_Year', 'PC4'],
1134.                                              values='Number_of_DOTS',
1135.                                              aggfunc=np.sum, fill_value=0)
1136.
1137.      # Create a pivot table with the population per zip code per year. Filter on age group 65-85.
1138.
1139.      Pop_CTA_Test_1415_1516 = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1140.
1141.      Pop_CTA_Test_1415_1516 = Pop_CTA_Test_1415_1516.drop(Pop_CTA_Test_1415_1516[
1142.                                              Pop_CTA_Test_1415_1516.Year == 2017].index)
1143.
1144.      Pop_CTA_Test_1415_1516 = Pop_CTA_Test_1415_1516.drop(Pop_CTA_Test_1415_1516[
1145.                                              Pop_CTA_Test_1415_1516.Year == 2016].index)
1146.
1147.      Pivot_Pop_CTA_Test_1415_1516 = Pop_CTA_Test_1415_1516[Pop_CTA_Test_1415_1516.Age_Group != "85+"].pivot_table(
1148.                                              index=['Year', 'PC4'],
1149.                                              values='Population',
1150.                                              aggfunc=np.sum, fill_value=0)
1151.
1152.      # Replace the pivot table with values of (the number of injurious falls / the population)*100 to create the outcome variable:

```

```

1153. # Number of Falls per 100 elderly (of age group 65-85).
1154.
1155. Falls_DividedBy_Pop_CTA_Test_1415_1516 = (Pivot_CTA_test_1415_1516.values[:,0]/Pivot_Pop_CTA_Test_1415_1516.values[:,0]) * 100
1156.
1157. # Add the index as a column.
1158.
1159. Pivot_CTA_test_1415_1516.reset_index(level=0, inplace=True)
1160. Pivot_CTA_test_1415_1516.reset_index(level=0, inplace=True)
1161.
1162. # Create definitions to create columns with the correct dummy values.
1163.
1164. def assign_dummy_region(PC4):
1165.     if ((PC4 > 3314) & (PC4 < 3316)):      # Stadspolders
1166.         return 1
1167.     elif ((PC4 > 3316) & (PC4 < 3320)):    # Sterrenburg (1), Dubbeldam, Crabbehof
1168.         return 1
1169.     elif ((PC4 > 3327) & (PC4 < 3329)):    # Sterrenburg (2nd zip code)
1170.         return 1
1171.     else:
1172.         return 0
1173.
1174. def assign_dummy_period_14_15(year):
1175.     if year == '2014-2015':
1176.         return 1
1177.     else:
1178.         return 0
1179. def assign_dummy_period_15_16(year):
1180.     if year == '2015-2016':
1181.         return 1
1182.     else:
1183.         return 0
1184. def assign_dummy_period_16_17(year):
1185.     if year == '2016-2017':
1186.         return 1
1187.     else:
1188.         return 0
1189. def assign_dummy_period_17_18(year):
1190.     if year == '2017-2018':
1191.         return 1
1192.     else:
1193.         return 0

```

```

1194. # Add dummy variables.
1195. Pivot_CTA_test_1415_1516['Ig'] = Pivot_CTA_test_1415_1516.PC4.apply(assign_dummy_region)
1196.
1197. Pivot_CTA_test_1415_1516['P1t'] = Pivot_CTA_test_1415_1516.Analysis_Year.apply(assign_dummy_period_15_16)
1198.
1199. Pivot_CTA_test_1415_1516['Ig * P1t'] = Pivot_CTA_test_1415_1516['Ig'] * Pivot_CTA_test_1415_1516['P1t']
1200.
1201. Pivot_CTA_test_1415_1516['# Falls per 100 Elderly'] = Pivot_CTA_test_1415_1516['Number_of_DOTS'] / Pivot_CTA_test_1415_1516['Population']
1202.
1203. # Add column with the population to the dataframe. The population per zipcode-area will be used as weight.
1204.
1205. Pivot_CTA_test_1415_1516['Population'] = Pivot_Pop_CTA_Test_1415_1516.values[:,0]
1206.
1207. CTA_Test_1415_1516_Falls_per_100_Elderly = pd.DataFrame(Falls_DividedBy_Pop_CTA_Test_1415_1516,columns =
1208.                                         ['CTA_Test_1415_1516_Falls_per_100_Elderly'])
1209.
1210. # Run the Weighted Least Squares (WLS) regression.
1211.
1212. y = CTA_Test_1415_1516_Falls_per_100_Elderly
1213. x = Pivot_CTA_test_1415_1516[['Ig','P1t','Ig * P1t']]
1214. Pop_65_85_CTA1 = Pivot_CTA_test_1415_1516.Population
1215. x = sm.add_constant(x)
1216.
1217. model = sm.WLS(y, x, weights=Pop_65_85_CTA1)
1218. results = model.fit()
1219.
1220. print(results.summary(alpha=0.1))
1221.
1222. # The coefficient of Ig * P1t is close to 0 and has a high p-value (0.80). This indicates that there is a similar trend
1223. # between the control- and intervention group in this pre-intervention period. Therefore, the CTA holds. However, it is
1224. # necessary to check whether the CTA holds for year 2015-2016 and 2016-2017. This will be done in the next section.
1225.
1226. # This section can be used to print a table with the data used to perform the DID analysis.
1227.
1228. # Pivot_CTA_test_1415_1516.rename(columns={'Number_of_DOTS':'# falls / 100 elderly'}, inplace=True)
1229. # Pivot_CTA_test_1415_1516['# falls / 100 elderly'] = CTA_Test_1415_1516_Falls_per_100_Elderly
1230. # img = Make_Pretty_Table(Pivot_CTA_test_1415_1516.round(3), header_columns=0, col_width=2.8)
1231.
1232. # In the next section, the difference in trends between year 2015-2016 and year 2016-2017 is determined.
1233.
1234. CTA_test_1516_1617 = DF_Falls_Case
1235.

```

```

1236. # A pivot table is created with the number of injurious falls per zip code per analysis year. Filter on age group 65-85.
1237. # For this analysis, it is necessary to remove the data in year 2017-2018.
1238.
1239. CTA_test_1516_1617 = CTA_test_1516_1617.drop(CTA_test_1516_1617[
1240.                                         CTA_test_1516_1617.Analysis_Year == '2017-2018'].index)
1241.
1242. Pivot_CTA_test_1516_1617 = CTA_test_1516_1617[CTA_test_1516_1617.Age_Group != "85+"].pivot_table(
1243.                                         index=['Analysis_Year', 'PC4'],
1244.                                         values='Number_of_DOTS',
1245.                                         aggfunc=np.sum, fill_value=0)
1246.
1247. # Create a pivot table with the population per zip code per year. Filter on age group 65-85.
1248.
1249. Pop_CTA_Test_1516_1617 = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1250.
1251. Pop_CTA_Test_1516_1617 = Pop_CTA_Test_1516_1617.drop(Pop_CTA_Test_1516_1617[
1252.                                         Pop_CTA_Test_1516_1617.Year == 2017].index)
1253.
1254. Pivot_Pop_CTA_Test_1516_1617 = Pop_CTA_Test_1516_1617[Pop_CTA_Test_1516_1617.Age_Group != "85+"].pivot_table(
1255.                                         index=['Year', 'PC4'],
1256.                                         values='Population',
1257.                                         aggfunc=np.sum, fill_value=0)
1258.
1259. # Replace the pivot table with values of (the number of injurious falls / the population)*100 to create the outcome variable:
1260. # Number of Falls per 100 elderly (of age group 65-85).
1261.
1262. Falls_DividedBy_Pop_CTA_Test_1516_1617 = (Pivot_CTA_test_1516_1617.values[:,0]/Pivot_Pop_CTA_Test_1516_1617.values[:,0]) * 100
1263.
1264. # Add the index as a column.
1265.
1266. Pivot_CTA_test_1516_1617.reset_index(level=0, inplace=True)
1267. Pivot_CTA_test_1516_1617.reset_index(level=0, inplace=True)
1268.
1269. # Add dummy variables.
1270.
1271. Pivot_CTA_test_1516_1617['Ig'] = Pivot_CTA_test_1516_1617.PC4.apply(assign_dummy_region)
1272.
1273. Pivot_CTA_test_1516_1617['P1t'] = Pivot_CTA_test_1516_1617.Analysis_Year.apply(assign_dummy_period_15_16)
1274. Pivot_CTA_test_1516_1617['P2t'] = Pivot_CTA_test_1516_1617.Analysis_Year.apply(assign_dummy_period_16_17)
1275.
1276. Pivot_CTA_test_1516_1617['Ig * P2t'] = Pivot_CTA_test_1516_1617['Ig'] * Pivot_CTA_test_1516_1617['P2t']

```

```

1277. # Add column with the population to the dataframe. The population per zipcode-area will be used as weight.
1278. Pivot_CTA_test_1516_1617['Population'] = Pivot_Pop_CTA_Test_1516_1617.values[:,0]
1279.
1280. CTA_Test_1516_1617_Falls_per_100_Elderly = pd.DataFrame(Falls_DividedBy_Pop_CTA_Test_1516_1617,columns =
1281.                                         ['CTA_Test_1516_1617_Falls_per_100_Elderly'])
1282.
1283.
1284. # Run the Weighted Least Squares (WLS) regression.
1285.
1286. y = CTA_Test_1516_1617_Falls_per_100_Elderly
1287. x = Pivot_CTA_test_1516_1617[['Ig','P1t','P2t','Ig * P2t']]
1288. Pop_65_85_CTA2 = Pivot_CTA_test_1516_1617.Population
1289. x = sm.add_constant(x)
1290.
1291. model = sm.WLS(y, x, weights=Pop_65_85_CTA2)
1292. results = model.fit()
1293.
1294.
1295. print(results.summary(alpha=0.1))
1296.
1297. # The coefficient of Ig * P1t is close to 0 and has a high p-value (0.94). This indicates that there is a similar trend
1298. # between the control- and intervention group in this pre-intervention period. Therefore, the CTA holds and the DID method
1299. # can be used to assess the effect of fall prevention programs on the number of injurious fall incidents. The effect will be
1300. # determined in the next section.
1301.
1302. ### Running Weighted Least Squares (WLS) Difference-in-
1303. Differences (DID) regression to determine effect of fall prevention programs on the number of injurious falls
1304.
1305. # As the common trend assumption holds true for elderly aged between 65 and 85, it is possible to perform a Difference-In-
1306. # Differences analysis using Weighted Least Squares (WLS) regression. The DID method is used to estimate the effect of a
1307. # treatment (such as a fall prevention program) by comparing the changes in outcomes over time between a population that is
1308. # enrolled in a program (the treatment group) and a population that is not (the control group). For more information: see
1309. # chapter 4. The following Difference-In-Difference (DID) estimating equation is used:
1310.
1311. #  $Y = x_0 + x_1 * Ig + x_2 * P1t + x_3 * P2t + x_4 * P3t + x_5 * (Ig * P3t) + E$ 
1312.
1313. # The coefficient x5 provides the Difference-in-Differences estimate. See for more information chapter 4.
1314. # In the following section, the data is prepared and the DID analysis is performed.
1315.
1316. # A pivot table is created with the number of injurious falls per zip code per analysis year. Filter on age group 65-85.
1317. DID_Analysis_65_85 = DF_Falls_Case

```

```

1318. Pivot_DID_Analysis_65_85 = DID_Analysis_65_85[DID_Analysis_65_85.Age_Group != "85+"].pivot_table(
1319.                                         index=['Analysis_Year', 'PC4'],
1320.                                         values='Number_of_DOTS',
1321.                                         aggfunc=np.sum, fill_value=0)
1322.
1323. # Create a pivot table with the population per zip code per year. Filter on age group 65-85.
1324.
1325. Popluation_DID_65_85 = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1326. Pivot_Population_65_85 = Popluation_DID_65_85[Popluation_DID_65_85.Age_Group != "85+"].pivot_table(
1327.                                         index=['Year', 'PC4'],
1328.                                         values='Population',
1329.                                         aggfunc=np.sum, fill_value=0)
1330.
1331. # Replace the pivot table with values of (the number of injurious falls / the population)*100 to create the outcome variable:
1332. # Number of Falls per 100 elderly (of age group 65-85).
1333.
1334. Falls_DividedBy_Pop_65_85 = (Pivot_DID_Analysis_65_85.values[:,0]/Pivot_Population_65_85.values[:,0]) * 100
1335.
1336. # Add the index as a column.
1337.
1338. Pivot_DID_Analysis_65_85.reset_index(level=0, inplace=True)
1339. Pivot_DID_Analysis_65_85.reset_index(level=0, inplace=True)
1340.
1341. # Add dummy variables.
1342.
1343. Pivot_DID_Analysis_65_85['Ig'] = Pivot_DID_Analysis_65_85.PC4.apply(assign_dummy_region)
1344.
1345. Pivot_DID_Analysis_65_85['P1t'] = Pivot_DID_Analysis_65_85.Analysis_Year.apply(assign_dummy_period_15_16)
1346. Pivot_DID_Analysis_65_85['P2t'] = Pivot_DID_Analysis_65_85.Analysis_Year.apply(assign_dummy_period_16_17)
1347. Pivot_DID_Analysis_65_85['P3t'] = Pivot_DID_Analysis_65_85.Analysis_Year.apply(assign_dummy_period_17_18)
1348.
1349. Pivot_DID_Analysis_65_85['Ig * P3t'] = Pivot_DID_Analysis_65_85['Ig'] * Pivot_DID_Analysis_65_85['P3t']
1350.
1351. # Add column with the population to the dataframe. The population per PC4-area will be used as weight.
1352.
1353. Pivot_DID_Analysis_65_85['Population'] = Pivot_Population_65_85.values[:,0]
1354.
1355. Falls_per_100_Elderly_65_85 = pd.DataFrame(Falls_DividedBy_Pop_65_85,columns=['Falls_per_100_Elderly_65_85'])
1356.
1357. # Run the Weighted Least Squares (WLS) regression.
1358.
1359. y = Falls_per_100_Elderly_65_85

```

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1360.     x = Pivot_DID_Analysis_65_85[['Ig','P1t','P2t','P3t','Ig * P3t']]
1361.     Pop_65_85 = Pivot_DID_Analysis_65_85.Population
1362.     x = sm.add_constant(x)
1363.
1364.     model = sm.WLS(y, x, weights=Pop_65_85)
1365.     results = model.fit()
1366.
1367.     print(results.summary(alpha=0.1))
1368.
1369.     ## Determining the effect of the programs on the severity of fall incidents
1370.
1371.     ##### Graph 1: visualizing the severity of the falls over the years
1372.
1373.     # Count the number of injurious fall incidents per classification for both groups in year 2016-2017 and 2017-2018.
1374.
1375.     DID_Analysis_16_18 = DF_Falls_Case.drop(DF_Falls_Case[
1376.                                                 DF_Falls_Case.Analysis_Year == '2014-2015'].index)
1377.     DID_Analysis_16_18 = DID_Analysis_16_18.drop(DID_Analysis_16_18[
1378.                                                 DID_Analysis_16_18.Analysis_Year == '2015-2016'].index)
1379.
1380.     # Prepare data for visualization.
1381.
1382.     Analysis_Severity_Class1 = np.array([
1383.         DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 1) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1384.         (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1385.         (
1386.             DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 1) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1387.             (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1388.         (
1389.             DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 1) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1390.             (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1391.         (
1392.             DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 1) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1393.             (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1394.     ])
1395.     Analysis_Severity_Class2 = np.array([
1396.         DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 2) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1397.             (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1398.         (
1399.             DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 2) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1400.             (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1401.         (

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1402. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 2) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1403. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1404. (
1405. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 2) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1406. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1407. ])
1408. Analysis_Severity_Class3 = np.array([
1409. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 3) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1410. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1411. (
1412. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 3) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1413. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1414. (
1415. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 3) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1416. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1417. (
1418. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 3) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1419. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1420. ])
1421. Analysis_Severity_Class4 = np.array([
1422. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 4) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1423. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1424. (
1425. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 4) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1426. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1427. (
1428. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 4) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1429. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1430. (
1431. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 4) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1432. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1433. ])
1434. Analysis_Severity_Class5 = np.array([
1435. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 5) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1436. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1437. (
1438. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 5) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1439. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1440. (
1441. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 5) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1442. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1443. (

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1444. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 5) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1445. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1446. ])
1447. Analysis_Severity_Class6 = np.array([
1448. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 6) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1449. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1450. (
1451. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 6) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1452. (DID_Analysis_16_18.Group == 'Control group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1453. (
1454. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 6) & (DID_Analysis_16_18.Analysis_Year == '2016-2017') &
1455. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() ),
1456. (
1457. DID_Analysis_16_18[(DID_Analysis_16_18.Classification == 6) & (DID_Analysis_16_18.Analysis_Year == '2017-2018') &
1458. (DID_Analysis_16_18.Group == 'Intervention group') & (DID_Analysis_16_18.Age_Group != '85+')].Classification.count() )
1459. ])
1460.
1461. # Subtract the total population of both groups in the analysis year from the dataset.
1462.
1463. Popluation_DID_16_18 = Popluation_DID_65_85.drop(Popluation_DID_65_85[
1464.                                         Popluation_DID_65_85.Year == 2014].index)
1465. Popluation_DID_16_18 = Popluation_DID_16_18.drop(Popluation_DID_16_18[
1466.                                         Popluation_DID_16_18.Year == 2015].index)
1467.
1468.
1469. Pivot_Popluation_DID_SA = Popluation_DID_16_18[Popluation_DID_16_18.Age_Group != "85+"].pivot_table(
1470.                                         index=['Group','Year'],
1471.                                         values='Population',
1472.                                         aggfunc=np.sum, fill_value=0)
1473.
1474. # Now it is possible to divide the number of falls of classification x of year y by the population of year y, to get the
1475. # outcome measure.
1476.
1477. Analysis_Severity_Class1 = ((Analysis_Severity_Class1) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1478. Analysis_Severity_Class2 = ((Analysis_Severity_Class2) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1479. Analysis_Severity_Class3 = ((Analysis_Severity_Class3) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1480. Analysis_Severity_Class4 = ((Analysis_Severity_Class4) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1481. Analysis_Severity_Class5 = ((Analysis_Severity_Class5) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1482. Analysis_Severity_Class6 = ((Analysis_Severity_Class6) / (Pivot_Popluation_DID_SA.values.flatten())).tolist()
1483.
1484. # Multiply every value to create the outcome variable number of injurious falls of severity x per 100 elderly.
1485.

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1486.     Analysis_Severity_Class1 = [i * 100 for i in Analysis_Severity_Class1]
1487.     Analysis_Severity_Class2 = [i * 100 for i in Analysis_Severity_Class2]
1488.     Analysis_Severity_Class3 = [i * 100 for i in Analysis_Severity_Class3]
1489.     Analysis_Severity_Class4 = [i * 100 for i in Analysis_Severity_Class4]
1490.     Analysis_Severity_Class5 = [i * 100 for i in Analysis_Severity_Class5]
1491.     Analysis_Severity_Class6 = [i * 100 for i in Analysis_Severity_Class6]
1492.
1493. # Plot stacked barchart to visualize the severity of the falls.
1494.
1495. Severity1 = go.Bar(
1496.     x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1497.         'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1498.     y=Analysis_Severity_Class1,
1499.     marker=dict(
1500.         color=[ 'RGB(166, 217, 106)', 'RGB(166, 217, 106)',
1501.             'RGB(166, 217, 106)', 'RGB(166, 217, 106)'],
1502.         name='Severity 1'
1503.     )
1504. Severity2 = go.Bar(
1505.     x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1506.         'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1507.     y=Analysis_Severity_Class2,
1508.     marker=dict(
1509.         color=[ 'RGB(217, 239, 139)', 'RGB(217, 239, 139)',
1510.             'RGB(217, 239, 139)', 'RGB(217, 239, 139)'],
1511.         name='Severity 2'
1512.     )
1513. Severity3 = go.Bar(
1514.     x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1515.         'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1516.     y=Analysis_Severity_Class3,
1517.     marker=dict(
1518.         color=[ 'RGB(254, 224, 139)', 'RGB(254, 224, 139)',
1519.             'RGB(254, 224, 139)', 'RGB(254, 224, 139)'],
1520.         name='Severity 3'
1521.     )
1522. Severity4 = go.Bar(
1523.     x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1524.         'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1525.     y=Analysis_Severity_Class4,
1526.     marker=dict(
1527.         color=[ 'RGB(253, 174, 97)', 'RGB(253, 174, 97)',
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1528.         'RGB(253, 174, 97)', 'RGB(253, 174, 97')]),
1529.         name='Severity 4'
1530.     )
1531.     Severity5 = go.Bar(
1532.         x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1533.             'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1534.         y=Analysis_Severity_Class5,
1535.         marker=dict(
1536.             color=['RGB(244, 109, 67)', 'RGB(244, 109, 67)',
1537.                 'RGB(244, 109, 67)', 'RGB(244, 109, 67')]),
1538.         name='Severity 5'
1539.     )
1540.     Severity6 = go.Bar(
1541.         x=['Control group:<br> 2016-2017', 'Control group:<br> 2017-2018',
1542.             'Intervention group:<br> 2016-2017', 'Intervention group:<br> 2017-2018'],
1543.         y=Analysis_Severity_Class6,
1544.         marker=dict(
1545.             color=['RGB(215, 48, 39)', 'RGB(215, 48, 39)',
1546.                 'RGB(215, 48, 39)', 'RGB(215, 48, 39')]),
1547.         name='Severity 6'
1548.     )
1549.
1550.     data = [Severity1, Severity2, Severity3, Severity4, Severity5, Severity6]
1551.     layout = go.Layout(
1552.         barmode='stack',
1553.         yaxis = dict(title = '# falls per 100 elderly (65-85)'),
1554.         font=dict(family='Calibri', size=14,
1555.                   color='rgb(67, 67, 67)'),
1556.     )
1557.
1558.     fig4 = go.Figure(data=data, layout=layout)
1559.     iplot(fig4, filename='stacked-bar')
1560.
1561.     # pio.write_image(fig4, 'Severity number of falls per 100 elderly 65-85.png')
1562.     # fig4.savefig('Severity analysis stacked bar.png', dpi=500, bbox_inches='tight')
1563.
1564.     ##### Graph 2: visualizing the relative differences in the severity of the falls over the years
1565.
1566.     # Calculate the sum of falls per 100 elderly in year 2016-2017 and 2017-2018 per group. As preparation for another graph to
1567.     # visualize the relative differences in the severity of the falls.
1568.
1569.

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1570.     Sum_ControlGroup_16_17 = Analysis_Severity_Class1[0] + Analysis_Severity_Class2[0] + Analysis_Severity_Class3[0] + \
1571.             Analysis_Severity_Class4[0] + Analysis_Severity_Class5[0] + Analysis_Severity_Class6[0]
1572.     Sum_ControlGroup_17_18 = Analysis_Severity_Class1[1] + Analysis_Severity_Class2[1] + Analysis_Severity_Class3[1] + \
1573.             Analysis_Severity_Class4[1] + Analysis_Severity_Class5[1] + Analysis_Severity_Class6[1]
1574.     Sum_InterventionGroup_16_17 = Analysis_Severity_Class1[2] + Analysis_Severity_Class2[2] + Analysis_Severity_Class3[2] + \
1575.             Analysis_Severity_Class4[2] + Analysis_Severity_Class5[2] + Analysis_Severity_Class6[2]
1576.     Sum_InterventionGroup_17_18 = Analysis_Severity_Class1[3] + Analysis_Severity_Class2[3] + Analysis_Severity_Class3[3] + \
1577.             Analysis_Severity_Class4[3] + Analysis_Severity_Class5[3] + Analysis_Severity_Class6[3]
1578.
1579. # Create a list with the percentages of the severity level per group and year.
1580.
1581. Percentage_ControlGroup_16_17 = [[(Analysis_Severity_Class1[0] / Sum_ControlGroup_16_17)] + \
1582.             [(Analysis_Severity_Class2[0] / Sum_ControlGroup_16_17)] + \
1583.             [(Analysis_Severity_Class3[0] / Sum_ControlGroup_16_17)] + \
1584.             [(Analysis_Severity_Class4[0] / Sum_ControlGroup_16_17)] + \
1585.             [(Analysis_Severity_Class5[0] / Sum_ControlGroup_16_17)] + \
1586.             [(Analysis_Severity_Class6[0] / Sum_ControlGroup_16_17)]]
1587. Percentage_ControlGroup_17_18 = [[(Analysis_Severity_Class1[1] / Sum_ControlGroup_17_18)] + \
1588.             [(Analysis_Severity_Class2[1] / Sum_ControlGroup_17_18)] + \
1589.             [(Analysis_Severity_Class3[1] / Sum_ControlGroup_17_18)] + \
1590.             [(Analysis_Severity_Class4[1] / Sum_ControlGroup_17_18)] + \
1591.             [(Analysis_Severity_Class5[1] / Sum_ControlGroup_17_18)] + \
1592.             [(Analysis_Severity_Class6[1] / Sum_ControlGroup_17_18)]]
1593. Percentage_InterventionGroup_16_17 = [[(Analysis_Severity_Class1[2] / Sum_InterventionGroup_16_17)] + \
1594.             [(Analysis_Severity_Class2[2] / Sum_InterventionGroup_16_17)] + \
1595.             [(Analysis_Severity_Class3[2] / Sum_InterventionGroup_16_17)] + \
1596.             [(Analysis_Severity_Class4[2] / Sum_InterventionGroup_16_17)] + \
1597.             [(Analysis_Severity_Class5[2] / Sum_InterventionGroup_16_17)] + \
1598.             [(Analysis_Severity_Class6[2] / Sum_InterventionGroup_16_17)]]
1599. Percentage_InterventionGroup_17_18 = [[(Analysis_Severity_Class1[3] / Sum_InterventionGroup_17_18)] + \
1600.             [(Analysis_Severity_Class2[3] / Sum_InterventionGroup_17_18)] + \
1601.             [(Analysis_Severity_Class3[3] / Sum_InterventionGroup_17_18)] + \
1602.             [(Analysis_Severity_Class4[3] / Sum_InterventionGroup_17_18)] + \
1603.             [(Analysis_Severity_Class5[3] / Sum_InterventionGroup_17_18)] + \
1604.             [(Analysis_Severity_Class6[3] / Sum_InterventionGroup_17_18)]]
1605.
1606. # Round the percentages.
1607.
1608. Percentage_ControlGroup_16_17[0] = [i * 100 for i in Percentage_ControlGroup_16_17[0]]
1609. Percentage_ControlGroup_16_17 = [ round(elem +0.1) for elem in Percentage_ControlGroup_16_17[0] ]
1610. Percentage_ControlGroup_17_18[0] = [i * 100 for i in Percentage_ControlGroup_17_18[0]]
1611. Percentage_ControlGroup_17_18 = [ round(elem) for elem in Percentage_ControlGroup_17_18[0] ]

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1612. Percentage_InterventionGroup_16_17[0] = [i * 100 for i in Percentage_InterventionGroup_16_17[0]]
1613. Percentage_InterventionGroup_16_17 = [ round(elem) for elem in Percentage_InterventionGroup_16_17[0] ] # To get sim round
1614. Percentage_InterventionGroup_17_18[0] = [i * 100 for i in Percentage_InterventionGroup_17_18[0]]
1615. Percentage_InterventionGroup_17_18 = [ round(elem + 0.1) for elem in Percentage_InterventionGroup_17_18[0] ]
1616.
1617. # Combine all the lists containing the percentages.
1618.
1619. List_Perc_groups = [Percentage_ControlGroup_17_18] + [Percentage_ControlGroup_16_17] + [Percentage_InterventionGroup_17_18]+\ \
1620.             [Percentage_InterventionGroup_16_17]
1621.
1622. # Plot a horizontal stacked bar chart to visualize the differences in the severity of the falls over the years.
1623.
1624. top_labels = ['Severity 1', 'Severity 2', 'Severity 3', '4', 'Severity 5', 'Severity 6']
1625.
1626. colors = ['RGB(166, 217, 106)', 'RGB(217, 239, 139)', \
1627.            'RGB(254, 224, 139)', 'RGB(253, 174, 97)', \
1628.            'RGB(244, 109, 67)', 'RGB(215, 48, 39)']
1629.
1630. x_data = List_Perc_groups
1631.
1632. y_data = ['Control group:<br> 2017-2018', 'Control group:<br> 2016-2017', \
1633.            'Intervention group:<br> 2017-2018' , 'Intervention group:<br> 2016-2017']
1634.
1635. traces = []
1636.
1637. for i in range(0, len(x_data[0])):
1638.     for xd, yd in zip(x_data, y_data):
1639.         traces.append(go.Bar(
1640.             x=[xd[i]],
1641.             y=[yd],
1642.             orientation='h',
1643.             marker=dict(
1644.                 color=colors[i],
1645.                 line=dict(
1646.                     color='rgb(248, 248, 249)',
1647.                     width=1)
1648.             )
1649.         ))
1650.
1651. layout = go.Layout(
1652.     autosize=False,
1653.     width=1000,

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1654.         height=500,
1655.         xaxis=dict(
1656.             showgrid=False,
1657.             showline=False,
1658.             showticklabels=False,
1659.             zeroline=False,
1660.             domain=[0.15, 1]
1661.         ),
1662.         yaxis=dict(
1663.             showgrid=False,
1664.             showline=False,
1665.             showticklabels=False,
1666.             zeroline=False,
1667.         ),
1668.         barmode='stack',
1669.         paper_bgcolor='rgb(255, 255, 255)',
1670.         plot_bgcolor='rgb(255, 255, 255)',
1671.         margin=dict(
1672.             l=120,
1673.             r=10,
1674.             t=140,
1675.             b=80
1676.         ),
1677.         showlegend=False,
1678.     )
1679.
1680.     annotations = []
1681.
1682.     for yd, xd in zip(y_data, x_data):
1683.         # labeling the y-axis.
1684.         annotations.append(dict(xref='paper', yref='y',
1685.                                 x=0.14, y=yd,
1686.                                 xanchor='right',
1687.                                 text=str(yd),
1688.                                 font=dict(family='Calibri', size=14,
1689.                                           color='rgb(67, 67, 67)'),
1690.                                 showarrow=False, align='right'))
1691.         # labeling the first percentage of each bar (x_axis).
1692.         annotations.append(dict(xref='x', yref='y',
1693.                                 x=xd[0] / 2, y=yd,
1694.                                 text=str(xd[0]) + '%',
1695.                                 font=dict(family='Calibri', size=14,

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1696.                                     color='rgb(248, 248, 255)'),
1697.                                     showarrow=False))
1698. # labeling the first Likert scale (on the top).
1699. if yd == y_data[-1]:
1700.     annotations.append(dict(xref='x', yref='paper',
1701.                               x=xd[0] / 2, y=1.1,
1702.                               text=top_labels[0],
1703.                               font=dict(family='Calibri', size=14,
1704.                                         color='rgb(67, 67, 67)'),
1705.                                         showarrow=False))
1706.     space = xd[0]
1707.     for i in range(1, len(xd)):
1708.         # labeling the rest of percentages for each bar (x_axis).
1709.         annotations.append(dict(xref='x', yref='y',
1710.                                   x=space + (xd[i]/2), y=yd,
1711.                                   text=str(xd[i]) + '%',
1712.                                   font=dict(family='Calibri', size=14,
1713.                                         color='rgb(255, 255, 255)'),
1714.                                         showarrow=False))
1715.         # labeling the Likert scale.
1716.         if yd == y_data[-1]:
1717.             annotations.append(dict(xref='x', yref='paper',
1718.                                       x=space + (xd[i]/2), y=1.1,
1719.                                       text=top_labels[i],
1720.                                       font=dict(family='Calibri', size=14,
1721.                                             color='rgb(67, 67, 67)'),
1722.                                             showarrow=False))
1723.     space += xd[i]
1724.
1725. layout['annotations'] = annotations
1726.
1727. fig5 = go.Figure(data=traces, layout=layout)
1728. iplot(fig5, filename='bar-colorscale')
1729.
1730. # pio.write_image(fig5, 'Severity analysis 65-85 vF.png')
1731.
1732. ## Determining the effect of the programs on the hospital costs
1733.
1734. ##### Plot the hospital expenditures per elderly per group over time
1735.
1736. # Create a pivot table with the total costs of DOTs per analysis-year and group, and exclude DOTs created for elderly above
1737. # age 85. This is because the fall prevention programs are designed for elderly between 65 and 85.

```

```

1738. # Use the dataset containing all the DOTs (not only the most severe one). In other words, instead of using dataset
1739. # "DF_Falls_Case", the dataset "ER_DOTs_Case" is used.
1740.
1741. Pivot_Costs_65_85 = ER_DOTs_Case[ER_DOTs_Case.Age_Group != "85+"].pivot_table(columns='Group',
1742.                                         index='Analysis_Year',
1743.                                         values='Final_DOT_Cost',
1744.                                         aggfunc=np.sum)
1745.
1746. # Create a pivot table with the population per group per year, and filter on age group 65-85.
1747.
1748. Pivot_Pop_DID_Costs = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"].pivot_table(columns='Group',
1749.                                         index='Year',
1750.                                         values='Population',
1751.                                         aggfunc=np.sum)
1752.
1753. # Replace the pivot table with values of (total costs of DOTs / the population) to create the outcome variable:
1754. # total (yearly) cost per elderly.
1755.
1756. Pivot_Costs_65_85[:] = Pivot_Costs_65_85.values / Pivot_Pop_DID_Costs.values
1757.
1758. # Plot the total costs of the DOTs over time for both groups (age group 65-85).
1759.
1760. # Prepare data for visualization.
1761.
1762. Control_group = go.Scatter(
1763.     x = ['2014-2015','2015-2016','2016-2017','2017-2018'],
1764.     y = [(Pivot_Costs_65_85.values.flatten()).tolist()[0], (Pivot_Costs_65_85.values.flatten()).tolist()[2],
1765.           (Pivot_Costs_65_85.values.flatten()).tolist()[4], (Pivot_Costs_65_85.values.flatten()).tolist()[6]],
1766.     name = 'Control Group',
1767.     line = dict(
1768.         color = ('rgba(219, 64, 82, 0.7)'),
1769.         width = 3)
1770. )
1771. Intervention_group = go.Scatter(
1772.     x = ['2014-2015','2015-2016','2016-2017','2017-2018'],
1773.     y = [(Pivot_Costs_65_85.values.flatten()).tolist()[1], (Pivot_Costs_65_85.values.flatten()).tolist()[3],
1774.           (Pivot_Costs_65_85.values.flatten()).tolist()[5], (Pivot_Costs_65_85.values.flatten()).tolist()[7]],
1775.     name = 'Intervention Group',
1776.     line = dict(
1777.         color = ('RGB(142,170,219)'),
1778.         width = 3)
1779. )

```

```

1780.     data = [Control_group, Intervention_group]
1781.
1782.     layout = go.Layout(
1783.         autosize=False,
1784.         width=1000,
1785.         height=500,
1786.         yaxis = dict(title = 'Hospital expenditures per elderly (65-85)',
1787.                     range = [0,100] ),
1788.         font=dict(family='Calibri', size=13.5,
1789.                     color='rgb(67, 67, 67)'))
1790.
1791.
1792.     fig8 = go.Figure(data=data, layout=layout)
1793. # iplot(fig8, filename='bar-colorscale')
1794. iplot(fig8, filename='basic-line')
1795.
1796. # pio.write_image(fig8, 'Plot_costs_65_85v7.png')
1797.
1798. # The common trend assumption does not hold and the DID method cannot be used to determine the effect of the fall prevention
1799. # programs on the hospital expenditures. However, a test is done to test the CTA. This will be done in the next section.
1800.
1801. ##### Test the CTA using the DID method in the pre-intervention period
1802.
1803. # In the next section, the difference in trends between year 2014-2015 and year 2015-2016 is determined.
1804.
1805. # A pivot table is created with the costs per zip code per analysis year. Filter on age group 65-85.
1806. # For this analysis, it is necessary to remove the data in year 2016-2017 and 2017-2018.
1807.
1808. DID_Analysis_65_85_cost = ER_DOTs_Case
1809.
1810. DID_Analysis_65_85_cost = DID_Analysis_65_85_cost.drop(DID_Analysis_65_85_cost[
1811.             DID_Analysis_65_85_cost.Analysis_Year == '2017-2018'].index)
1812.
1813. DID_Analysis_65_85_cost = DID_Analysis_65_85_cost.drop(DID_Analysis_65_85_cost[
1814.             DID_Analysis_65_85_cost.Analysis_Year == '2016-2017'].index)
1815.
1816. Pivot_DID_Analysis_65_85_cost = DID_Analysis_65_85_cost[DID_Analysis_65_85_cost.Age_Group != "85+"].pivot_table(
1817.             index=['Analysis_Year', 'PC4'],
1818.             values='Final_DOT_Cost',
1819.             aggfunc=np.sum, fill_value=0)
1820.
1821. # Create a pivot table with the population per zip code per year. Filter on age group 65-85.

```

```

1822.
1823.     Popluation_DID_65_85_cost = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1824.
1825.     Popluation_DID_65_85_cost = Popluation_DID_65_85_cost.drop(Popluation_DID_65_85_cost[
1826.                     Popluation_DID_65_85_cost.Year == 2017].index)
1827.
1828.     Popluation_DID_65_85_cost = Popluation_DID_65_85_cost.drop(Popluation_DID_65_85_cost[
1829.                     Popluation_DID_65_85_cost.Year == 2016].index)
1830.
1831.     Pivot_Population_65_85_cost = Popluation_DID_65_85_cost[Popluation_DID_65_85_cost.Age_Group != "85+"].pivot_table(
1832.                     index=['Year', 'PC4'],
1833.                     values='Population',
1834.                     aggfunc=np.sum, fill_value=0)
1835.
1836. # Replace the pivot table with values of (total costs of DOTs / the population) to create the outcome variable:
1837. # total (yearly) cost per elderly.
1838.
1839. Costs_DividedBy_Pop_65_85 = Pivot_DID_Analysis_65_85_cost.values[:,0]/Pivot_Population_65_85_cost.values[:,0]
1840.
1841. # Add the index as a column.
1842.
1843. Pivot_DID_Analysis_65_85_cost.reset_index(level=0, inplace=True)
1844. Pivot_DID_Analysis_65_85_cost.reset_index(level=0, inplace=True)
1845.
1846. # Add dummy variables.
1847.
1848. Pivot_DID_Analysis_65_85_cost['Ig'] = Pivot_DID_Analysis_65_85_cost.PC4.apply(assign_dummy_region)
1849.
1850. Pivot_DID_Analysis_65_85_cost['P1t'] = Pivot_DID_Analysis_65_85_cost.Analysis_Year.apply(assign_dummy_period_15_16)
1851.
1852. Pivot_DID_Analysis_65_85_cost['Ig * P1t'] = Pivot_DID_Analysis_65_85_cost['Ig'] * Pivot_DID_Analysis_65_85_cost['P1t']
1853.
1854. # Add column with the population to the dataframe. The population per zipcode-area will be used as weight.
1855.
1856. Pivot_DID_Analysis_65_85_cost['Population'] = Pivot_Population_65_85_cost.values[:,0]
1857.
1858. CTA_Test_1415_1516_Costs_per_Elderly = pd.DataFrame(Costs_DividedBy_Pop_65_85,columns =
1859.                                         ['CTA_Test_1415_1516_Costs_per_Elderly'])
1860.
1861. # Run the Weighted Least Squares (WLS) regression.
1862.
1863. y = CTA_Test_1415_1516_Costs_per_Elderly

```

```

1864.     x = Pivot_DID_Analysis_65_85_cost[['Ig','P1t','Ig * P1t']]
1865.     Pop_65_85_cost1 = Pivot_Population_65_85_cost.Population
1866.     x = sm.add_constant(x)
1867.
1868.     model = sm.WLS(y, x, weights=Pop_65_85_cost1)
1869.     results = model.fit()
1870.
1871.     print(results.summary(alpha=0.1))
1872.
1873.     # In the next section, the difference in trends between year 2015-2016 and year 2016-2017 is determined.
1874.
1875.     # A pivot table is created with the costs per zip code per analysis year. Filter on age group 65-85.
1876.     # For this analysis, it is necessary to remove the data in year 2017-2018.
1877.
1878.     DID_Analysis_65_85_cost = ER_DOTS_Case
1879.
1880.     DID_Analysis_65_85_cost = DID_Analysis_65_85_cost.drop(DID_Analysis_65_85_cost[
1881.                                         DID_Analysis_65_85_cost.Analysis_Year == '2017-2018'].index)
1882.
1883.     Pivot_DID_Analysis_65_85_cost = DID_Analysis_65_85_cost[DID_Analysis_65_85_cost.Age_Group != "85+"].pivot_table(
1884.                                         index=['Analysis_Year', 'PC4'],
1885.                                         values='Final_DOT_Cost',
1886.                                         aggfunc=np.sum, fill_value=0)
1887.
1888.     # Create a pivot table with the population per zip code per year. Filter on age group 65-85.
1889.
1890.     Population_DID_65_85_cost = Pop_Combined_Dord[Pop_Combined_Dord.Age_Group != "85+"]
1891.
1892.     Population_DID_65_85_cost = Population_DID_65_85_cost.drop(Population_DID_65_85_cost[
1893.                                         Population_DID_65_85_cost.Year == 2017].index)
1894.
1895.     Pivot_Population_65_85_cost = Population_DID_65_85_cost[Population_DID_65_85_cost.Age_Group != "85+"].pivot_table(
1896.                                         index=['Year', 'PC4'],
1897.                                         values='Population',
1898.                                         aggfunc=np.sum, fill_value=0)
1899.
1900.     # Replace the pivot table with values of (total costs of DOTs / the population) to create the outcome variable:
1901.     # total (yearly) cost per elderly.
1902.
1903.     Costs_DividedBy_Pop_65_85 = Pivot_DID_Analysis_65_85_cost.values[:,0]/Pivot_Population_65_85_cost.values[:,0]
1904.
1905.     # Add the index as a column.

```

```

1906.
1907. Pivot_DID_Analysis_65_85_cost.reset_index(level=0, inplace=True)
1908. Pivot_DID_Analysis_65_85_cost.reset_index(level=0, inplace=True)
1909.
1910. # Add dummy variables.
1911.
1912. Pivot_DID_Analysis_65_85_cost['Ig'] = Pivot_DID_Analysis_65_85_cost.PC4.apply(assign_dummy_region)
1913.
1914. Pivot_DID_Analysis_65_85_cost['P1t'] = Pivot_DID_Analysis_65_85_cost.Analysis_Year.apply(assign_dummy_period_15_16)
1915. Pivot_DID_Analysis_65_85_cost['P2t'] = Pivot_DID_Analysis_65_85_cost.Analysis_Year.apply(assign_dummy_period_16_17)
1916.
1917. Pivot_DID_Analysis_65_85_cost['Ig * P2t'] = Pivot_DID_Analysis_65_85_cost['Ig'] * Pivot_DID_Analysis_65_85_cost['P2t']
1918.
1919. # Add column with the population to the dataframe. The population per zipcode-area will be used as weight.
1920.
1921. Pivot_DID_Analysis_65_85_cost['Population'] = Pivot_Population_65_85_cost.values[:,0]
1922.
1923. CTA_Test_1516_1617_Costs_per_Elderly = pd.DataFrame(Costs_DividedBy_Pop_65_85,columns =
1924.                                     ['CTA_Test_1516_1617_Costs_per_Elderly'])
1925.
1926. # Run the Weighted Least Squares (WLS) regression.
1927.
1928. y = CTA_Test_1516_1617_Costs_per_Elderly
1929. x = Pivot_DID_Analysis_65_85_cost[['Ig','P1t','P2t','Ig * P2t']]
1930. Pop_65_85_cost2 = Pivot_Population_65_85_cost.Population
1931. x = sm.add_constant(x)
1932.
1933. model = sm.WLS(y, x, weights=Pop_65_85_cost2)
1934. results = model.fit()
1935.
1936. print(results.summary(alpha=0.1))
1937.
1938. # The coefficient of Ig * P2t is positive in pre-intervention year 2016-2017 and has a low p-value (0.10). This indicates that
1939. # there is a difference in the trend between the control- and intervention group in a pre-intervention period. Therefore, the
1940. # CTA does not hold and the DID method cannot be used to assess the effect of fall prevention programs on the hospital
1941. # expenditures in this specific case. In chapter 6 of the report, an explanation is given why the CTA does not hold. Also,
1942. # an alternative way to estimate the effect of fall prevention programs on the total healthcare expenditures is described
1943. # and those results are shown.
1944.
1945. ## Create table with demographic data of all regions for Appendix
1946.
1947. # Add a column indicating the region of the zip code area and create a pivot table.

```

```
1948. Pop_Combined_Dord[ 'Region' ] = Pop_Combined_Dord.PC4.apply(assign_region)
1949.
1950.
1951. Pivot_Population_All_Groups = Pop_Combined_Dord.pivot_table(columns='Region',
1952.                                         index=[ 'Year', 'Age_Group'],
1953.                                         values='Population',
1954.                                         aggfunc=np.sum, fill_value=0)
1955.
1956. # Set CSS properties for th elements in dataframe.
1957.
1958. th_props = [
1959.     ('font-size', '12px'),
1960.     ('text-align', 'center'),
1961.     ('font-weight', 'bold'),
1962.     ('color', 'black'),
1963.     ('background-color', '#f7f7f9')
1964. ]
1965.
1966. # Set CSS properties for td elements in dataframe.
1967.
1968. td_props = [
1969.     ('font-size', '11px')
1970. ]
1971.
1972. # Set table styles.
1973. styles = [
1974.     dict(selector="th", props=th_props),
1975.     dict(selector="td", props=td_props)
1976. ]
1977.
1978. Pivot_Population_All_Groups.style.set_table_styles(styles)
```