Economic Implications of Disability Prevention:

A Benefit-Cost Analysis of Targeted Occupational Health Interventions

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Abstract

Disability imposes personal suffering but also economic consequences for individuals, employers, and the society. Finding an optimal method for disability prevention can be considered beneficial and increasingly important for a country with a prominent public sector and a weakening labor force participation rate like Finland. Previous studies show evidence of the effectiveness of worksite health promotion programs that target care for employees who face a high risk for disability. Evidence shows positive cost-effectiveness of targeted occupational health interventions in preventing short-term disability but a wider benefit-cost analysis of targeted occupational health interventions with a view on both short-term and long-term disability prevention has not previously been conducted.

This study untangles the treatment effect of targeted occupational health interventions on societal net benefits resulted from disability prevention. Short-term disability as a concept is viewed through sickness absence, and long-term disability is represented by the disability benefits granted by the Finnish disability benefit system. The costs of disability preventing actions are limited to health care utilization. The research setting of this study has been observational, and the empirical analysis is conducted as a retrospective review of prospectively collected register data. The data registers cover health and disability related information of over 20,000 employees in Finland. In the main analysis, 1,679 treated employees identified with a high risk for disability are compared to 2,107 untreated high-risk employees. The benefit-cost analysis is constructed with the Average Treatment Effect framework combined with Net Benefits framework. The treatment of the framework of this study is an attendance to a targeted, pre-planned health check after an occupational health survey. The outcome of the framework is the net benefits that result from prevention of sickness absence workdays and granted disability benefits, and the investment costs resulted from health care utilization. The results are formed with Analysis of Covariance. Other methods to conduct the empirical analysis include polynomial regression, Multiple Imputation of Chained Equations, Propensity Scores, and Inverse Probability Weighting.

The results of this study show that targeted occupational health interventions are likely to impose positive net benefits to the society. The Average Treatment Effect on the net benefits of high-risk employees, 1,875 euros with a 95% confidence interval from -759 to 4,509 euros (p-value: .155) (ANCOVA), can be considered worthwhile to the society. In the research setting, the net benefits were in practice gained from the prevention of long-term disability. The treatment was not effective on the costs of short-term disability or the total health care utilization costs per employee. Sensitivity analyses indicate that targeted occupational health interventions are not on average effective when predicted to employees without a disability risk.

Keywords

health economics, disability, sickness absence, treatment effect, occupational health care, targeted intervention

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Abstract

Työkyvyttömyydestä koituu paitsi kärsimystä myös taloudellisia seurauksia yksilöille, työnantajille ja yhteiskunnalle. Työkyvyttömyyden ehkäisyä voi pitää erityisen merkityksellisenä ja hyödyllisenä Suomen kaltaiselle maalle, jonka haasteisiin sisältyy merkittävän julkisen sektorin ylläpito laskevassa työvoiman osallistumisasteessa. Aiemmat tutkimukset osoittavat, että terveyden edistämistä tukevat ohjelmat työpaikoilla voivat ehkäistä työkyvyttömyyttä kohdistettuina työkyvyttömyysriskissä oleville henkilöille. Kohdistetuista työterveysinterventioista on voitu aiemmin osoittaa positiivista kustannusvaikuttavuutta lyhytaikaiseen työkyvyttömyyteen. Laajempaa hyöty-kustannus-analyysiä ei kohdistetuista työterveysinterventioista ole kuitenkaan aiemmin tehty, eikä kohdistettuja työterveysinterventioita ole aiemmin tarkasteltu samanaikaisesti sekä lyhyt- että pitkäaikaisen työkyvyttömyyden näkökulmista.

Tässä tutkimuksessa tarkastellaan kohdistettujen työterveysinterventioiden vaikutusta työkyvyttömyyden ehkäisystä muodostuviin yhteiskunnallisiin nettohyötyihin. Lyhytaikaista työkyvyttömyyttä tarkastellaan sairauspoissaolojen avulla, ja pitkäaikaista työkyvyttömyyttä edustavat työkyvyttömyysjärjestelmän työkyvyttömyysetuudet. Työkyvyttömyyden ehkäisyn toimenpiteet ja kustannukset on rajattu tutkimuksessa terveydenhuollon palvelujen käyttöön. Tutkimus on seurantatutkimus, ja empiirinen analyysi muodostetaan retrospektiivisenä tarkasteluna prospektiivisesti kerätystä rekisteriaineistosta. Aineisto käsittää terveys- ja työkyvyttömyystietoja yli 20 000 työntekijältä Suomessa. Pääanalyysissa 1 679 hoidettua työntekijää, joille on tunnistettu korkea työkyvyttömyysriski, verrataan 2 107 hoitamattomaan korkean riskin työntekijään. Hyöty-kustannus-analyysissä yhdistetään keskimääräisen hoitovaikutuksen (Average Treatment Effect) ja nettohyötyjen (Net Benefits) viitekehykset. Tulokset muodostetaan kovarianssianalyysillä (ANCOVA). Muita työssä hyödynnettäviä menetelmiä ovat polynomiregressio, MICE-moni-imputointialgoritmi (Multiple Imputation of Chained Equations), propensiteettipisteytys (Propensity Score), ja Inverse Probability Weighting -painotusmenetelmä.

Tutkimuksen tulokset osoittavat, että kohdistettujen työterveysinterventioiden yhteiskunnallinen vaikutus on todennäköisesti positiivinen: keskimääräinen hoitovaikutus nettohyötyihin korkean riskin työntekijää kohden, 1 875 euroa ja tämän 95 prosentin luottamusväli -759 eurosta 4 509 euroon (p-arvo: 0,155) (ANCOVA) osoittavat, että kohdistettuja työterveysinterventioita voi pitää keskimäärin yhteiskunnallisesti kannattavina. Tutkimusasetelmassa muodostuneet nettohyödyt olivat käytännössä täysin peräisin pitkäaikaisen työkyvyttömyyden ehkäisystä. Interventiolla ei ollut vaikutusta lyhytaikaisen työkyvyttömyyden kustannuksiin tai käytettyjen terveydenhuollon palvelujen kustannuksiin. Herkkyysanalyysi osoittaa, että kohdistetut työterveysinterventiot eivät ole keskimäärin vaikuttavia, kun ne kohdistetaan työntekijöille, joille ei ole tunnistettu työkyvyttömyysriskiä.

Avainsanat

terveystaloustiede, työkyvyttömyys, sairauspoissaolot, keskimääräinen hoitovaikutus, työterveyshuolto, kohdistettu interventio

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Chapter 1

Introduction

Disability imposes personal suffering but also economic consequences for individuals, employers, and the society. For example, the losses of potential work inputs due to persons on disability pensions reached 8 billion euros for Finland in the year 2012 (Rissanen & Kaseva 2014). The increased efforts in disability prevention have decreased the usage of disability benefits In Finland during the 2000s but this development showed a turnaround in 2018 as the number of granted disability benefits increased by seven percent (Kannisto 2019). Therefore, finding an optimal method for disability prevention can be considered beneficial and increasingly important for a country with large public sector like Finland.

Occupational health care offers means to prevent disability-causing diseases (Martimo & Antti-Poika 2000). Studies show that these diseases such as musculoskeletal and mental diseases can be predicted (Lusa, Miranda, Luukkonen & Punakallio 2015) (Roelen, Hoedeman, van Rhenen, Groothoff, Klink, L & Bültmann 2014) (Andersen, Clausen, Mortensen, Burr & Holtermann 2012) (Vita, Terry, Hubert & Fries 1998), and that health care actions targeted for employees with high risk for disability reduce sickness absence (Sauni & Leino 2016) (Taimela, Aronen, Malmivaara, Sintonen, Tiekso & Aro 2010). Occupational health care that in Finland is paid by the employers to support the employees' work ability, sometimes includes standardized processes and programs for disability treatment and prevention. Intervention and health care utilization, however, incur costs as well (Bültmann, Sherson, Olsen, Lysbeck Hansen, Lund & Kilsgaard 2009). Evaluating the effectiveness of different occupational health care programs in increasing work inputs in the society in relation to the costs of these programs can help employers target and organize occupational health care in a more efficient manner.

Targeted occupational health interventions are programs where employers aim to target preventive care for employees that have been identified with a high risk for disability. Health surveys where the employees self-assess the state of their health are one method to evaluate the disability risk for each employee. The answers of the survey are analyzed and some of the employees are invited to a health check that will be planned according to the risk elements found based on the survey. Previous studies show that targeted occupational health interventions show positive impact in reducing loss of work inputs (Taimela, Malmivaara, Justén, Läärä, Sintonen, Tiekso & Aro 2008) (Taimela, Lr, Malmivaara, Tiekso, Sintonen, Justn & Aro 2007) (Reijonsaari, Vehtari, van Mechelen, Aro & Taimela 2009), but a wider benefit-cost analysis of these programs had not been previously conducted. Most of the economic research on disability prevention analyze the cost-effectiveness of the disability-preventing interventions rather than the monetary net benefits. Moreover, most of the previous cost-effectiveness research on disability prevention focuses on either short-term or long-term disability or on disability related to specific diseases.

The objective of the present study was to analyze the net benefits of targeted occupational health interventions in disability prevention. The perspective of the study was societal and disability was viewed as a concept that included both short-term and long-term disability. Short-term disability was represented by sickness absence and long-term disability was represented by the disability benefits granted by the national disability benefit system. The main research question of the present study was: What are the net benefits of targeted occupational health interventions in reducing sickness absence and disability benefits? The results of the study were derived as monetary net benefits and the analysis was not limited to specific diseases. Therefore the present study complements the previous literature by producing beneficial information on disability prevention with a more comprehensive scope and more economic perspective.

A quantitative empirical analysis was conducted to answer the main research question. The analysis was conducted as a retrospective review of prospectively collected register data. The net benefits of targeted occupational health interventions were formulated with the Treatment Effect framework (Austin 2011) where the economic benefits resulting from the increase of work inputs were compared to the disability prediction costs and health care utilization costs. The preliminary hypothesis was that the treatment (an attendance to a targeted occupational health intervention) is cost-beneficial in reducing sickness absence days and disability benefits when compared to the control treatment (no attendance to any occupational health intervention). The results of the empirical analysis supported the hypothesis: targeted occupational health interventions were net beneficial for the society. The results indicated that most of the benefits result from prevention of long-term disability. The treatment was not effective on the net benefits of short-term disability, or the investment costs resulted from healthcase utilization.

After this introductory chapter, the study continues as follows. Chapter 2 presents a literature review of empirical studies in disability prevention. Chapter 3 describes the institutional setting of the present study, including how the costs of disability are formed in Finland and how Finnish employers and occupational health service providers cooperate to prevent disability. Chapter 4 presents the research methodology and the quantitative methods used. Chapter 5 presents the data, frameworks and models used in the present study. Chapter 6 presents the empirical results, and finally, Chapter 7 discusses the findings and proposes suggestions for the conclusions of the present study.

Chapter 2

Literature review

A prominent public sector and a weakening labor force participation rate are some of the special features of Finland. The government spending on public finances such as pensions, health care, and education can be considered relatively high. The aging population and the rising number of pensioners during the 2000s have been strongly weakening the labor force participation rate in the country (Vartiainen 2013) (Kinnunen & Mäki-Fränti 2011). The development of the dependency ratio has been a common concern during the 2000's and 2010's in Finland (Vartiainen 2013) (Kinnunen & Mäki-Fränti 2011) (Honkatukia, Ahokas & Marttila 2010).

One method to restrain the deteriorating dependency ratio and increase a nation's wealth is to influence in disability-related loss of potential work inputs (Vartiainen 2013). In Finland disability benefits that can be divided to disability pensions and rehabilitation benefits represent the most central route for early retirement and therefore impose losses of potential work inputs worth of billions of euros (Laaksonen, Rantala, Järnefelt & Kannisto 2016) (Rissanen & Kaseva 2014). Finland's Ministry of Social Affairs and Wealth has estimated the direct costs of the losses of potential work inputs due to persons on disability benefits as 8 billion euros in 2012 (Rissanen & Kaseva 2014). In 2014 seven percent of the working age were on a disability pension or a rehabilitation benefit (Laaksonen et al. 2016).

Disability prevention has been researched from numerous perspective in Finland and internationally for decades. Previous studies show that disability can be predicted and could be prevented by offering early treatment, rehabilitation and close monitoring when symptoms of disability occur (Laaksonen et al. 2016) (Davis, Smith, Ferguson, Stephens & Gianopoulos 2007). According to previous studies, disability is highly related to comorbidities, or several simultaneous chronic conditions (Fried, Ferrucci, Darer, Williamson & Anderson 2004) (Verbrugge, Lepkowski & Imanaka 1989). Predicting disability is sometimes challenging because sometimes disability develops due to accidents, and the severity of some disability cases develop steeper than the others (Ferrucci, Guralnik, Simonsick, Salive, Corti & Langlois 1996).

Since disability causes losses of potential work inputs, the focus of the previous research on disability prevention has naturally been on preventative actions at the worksites or on occupational health care (Goetzel & Ozminkowski 2008). Some studies show evidence of the effectiveness of targeted occupational health interventions (e.g. Taimela et al. 2010, 2008, 2007). However, most of the health economic research on disability prevention focus on the cost-effectiveness or cost-benefits of short-term disability prevention. These research have typically been focused only on specific diseases rather than disability as a whole. Analyses on the effectiveness on long-term disability prevention exist as well, but these do not offer information on the long-term net benefits of targeted occupational health interventions on a societal level.

Research on Worksite Health Promotion programs (WHP) began increasingly popular after the late-1980s, focusing on "factors that influence the health and productivity of workers" (Goetzel & Ozminkowski 2008). Worksite Health Promotion programs incorporate encouragement for healthy lifestyle behavior but also disease prevention in terms of screening, treatment and follow-up that is directed at individuals who face a high risk for disability due to lifestyle behavior or state of health. Goetzel and Ozminkowski (2008) conducted a literature review to address the employers' incentives to invest in WHP programs and to describe the characteristics of a successful WHP program. They argue that many employers may be reluctant to believe that the health promotion programs can produce a positive return on investment and therefore cost-benefit analyses or benefit-cost analyses of WHP programs could increase the engagement of organizations in actions to improve the employees' health. Goetzel and Ozminkowski (2008) summarize that the research from the 1980s and the early 1990s estimated a positive ROI of 40 percent to 214 percent. However, the quality of these studies were stated as suboptimal, and negative results were not likely to be reported. Goetzel and Ozminkowski (2008) therefore argue that to remain sustainable and attractive investments for the employers, WHP programs need to produce more information that support their cost-effectiveness or cost-benefit.

Worksite Health Promotion programs stand as a wide concept that, in addition to disability prevention, aims to promote employees' overall well-being and includes also other actions besides occupational health care. The focus of the research on WHPs has been restricted to medical interventions of occupational health care that aim to reduce short-term or long-term disability. A high number of studies exist that focus on the effectiveness of occupational health care in disability prevention, the relationships between disability-causing diseases and sickness absence, disability pensions, and even mortality. Van der Kink et al. (2001) conducted a quantitative meta-analysis to determine the effectiveness of occupational stress-reducing interventions and populations that would benefit the most from these kind of interventions. They state that interventions for stress management in general are effective, and that cognitive-behavioral interventions are more effective than relaxation techniques, multimodal programs, or organization-focused programs. Gjesdal et al. (2009) examined mortality among men and women with long term sickness absence with musculoskeletal or mental diseases. They applied a prospective cohort study to analyze if differences in mortality occurred depending on whether a person had been granted a disability pension or not. Based on the results they concluded that when monitoring employees with long-term sickness absence, the mortality among those who have been granted disability pensions are higher. Such research offers beneficial information on the motivation behind disability prevention but does not yet provide support for the employers to plan and optimize their disability preventive investments.

Effectiveness of treatments on reducing disability and especially sickness absence has been studied for various intervention types such as return-to-work programs. For example, Fleten and Johnsen (2006) studied the change in sickness absence by offering a minimal intervention by using randomized controlled trials. In their research setting, employees in the intervention group were contacted with an information letter and a questionnaire after the employee's sick leave had passed 14 days. The results, however, were significant for only part of the employees: those employees with mental disorders were more likely to return to work after the intervention but those with musculoskeletal diseases were less likely to return to work.

Return-to-work programs have also been studied by Bultmann et al. (2009) who conducted an economic evaluation of employees on sick leave due to musculoskeletal disorders in Denmark. They constructed a randomized controlled trial where employees on sick leave for 4 to 12 weeks were assigned to an intervention group or to a control group. The individuals in the intervention group were offered personalized treatment and return-to-work plans. The intervention group presented cost savings of USD 1 366 per person during the 6-month follow-up period, and USD 10 666 per person during the 12-month follow-up period when calculated in the sickness absence days. Bultmann et al. (2009) conclude that coordinated and tailored work rehabilitation appears cost-beneficial for the society.

Research on return-to-work programs and the research targeted for employees who already have suffered from short-term disability do provide beneficial information of the relationships between short-term and long-term disability. However, as Vaez et al. (2007) show in their prospective cohort study, employees that suffer from long sick leaves due to psychiatric disorders do not necessarily show high sickness absence amounts before the need for treatments strike. Therefore, return-to-work programs do not necessarily help those employers that aim for comprehensive and predictive care, to prevent disability before long-term sickness absence occurs.

Targeted occupational health interventions have previously been shown to reduce disability effectively and predictively. In these interventions, employees screened as high-risk employees for disability are invited to a health check, followed by tailored health plans jointly designed with the employee according to the findings during the intervention (Sauni & Leino 2016). Targeted occupational health interventions have become increasingly popular in Finland, and evidence of the effectiveness of these interventions have been gained from e.g. the research by Taimela et al. (2010) (2008) (2007) who state that targeting care for employees with high risk for disability decreases sickness absence. De Boer et al. (2004) show targeted occupational health interventions also promising in decreasing disability-related early retirement. At the same time untargeted health checks have not been shown to affect on long-term health indicators such as disability or mortality (Martimo & Antti-Poika 2000).

In case of targeted occupational health interventions, employees' disability risks are typically screened with health surveys (Sauni & Leino 2016). The health surveys aim to predict the employees' disability risk levels and find especially those individuals that show the highest risk for disability. During the 2000s, the use of surveys to identify the high-risk employees has become increasingly common, but the research on the performance of such surveys still remains relatively low. Some follow-up studies have shown how these surveys have succeeded in predicting the disability risks according to the state of health, in particular the conditions of the musculoskeletal system and mental health (Andersen et al. 2012) (Taimela et al. 2007) (van Hoffen, Joling, Heymans, Twisk & Roelen 2015). Standardized surveys can be considered improving the quality of health checks especially in recognizing the underlying threats for work disability and selecting the relevant health care actions. The surveys enable planning and structuring the health check beforehand to focus on the relevant risk factors identified. It has been shown that targeted occupational health interventions are especially effective for those employees who no longer believe in their own work abilities, who have at least one comorbidity (more than one simultaneous disability-predictive finding), or who suffer from significant musculoskeletal problems (Taimela et al. 2010).

Taimela et al. (2008) evaluated the effectiveness of two targeted occupational health intervention programs in reducing sickness absence of high-risk employees with randomized controlled trials. The screening of the employees was conducted via health surveys, and altogether 1342 employees were assigned to 3 groups according to their risk for sickness absence identified. The risk was evaluated based on the employee's health problems, including pain, musculoskeletal issues, depressive symptoms, sleep alertness and uncertainty about their own working ability. Two separate trials were conducted, one for the high-risk group, and the other for the intermediate-risk group. The employees in the high-risk group (n = 418) were randomly assigned to an intervention group and a control group, as well as the employees in the intermediate-risk group (n = 537). The results found that the trial for the high-risk group was effective; the mean sickness absence of the intervention group was 19.3, which was 35 percent lower than the mean of the control group (29.9 days). Moreover, the health care utilization costs were lower for the intervention group, even though the number of health care services used was higher compared to the control group. Taimela et al. (2008) concluded that this probably resulted because the care was assigned to employees predictively such that the potential greater use of health services in the future was avoided. However, the trial for the intermediate-risk group, including health advice by phone only, was not effective.

Taimela et al. (2008) (2007) conclude that targeting occupational health interventions for employees with high risks for short-term disability can reduce potential losses of work inputs with an effectiveness that is likely to be cost-beneficial. A more accurate benefit-cost analysis of targeted occupational health interventions, however, has remained to be conducted.

Hlobib et al. (Hlobil, Uegaki, Staal, de Bruyne, Smid & van Mechelen 2007) constructed a cost-benefit analysis of adjusting employees' tasks according to their level of function. They constructed a randomized controlled trial to examine the costs and benefits of comparing a graded activity intervention to usual care for employees with low-back pain. Altogether 134 employees were randomly assigned to a graded activity group and to a group with usual care. At the end of the treatment year, the graded activity group showed health care utilization costs of 83 euros higher than the group with usual care, but their reduction of productivity losses yielded an average savings of at least 999 euros. During the three-year follow-up time, their cumulative net benefits had yielded an average savings of 1 661 euros per employee. Hlobib et al. (Hlobil et al. 2007) conclude that offering graded activity for employees with musculoskeletal diseases such as low back pain can increase the efficiency of work inputs cost-beneficially. However, the analysis was narrowed to only those employees with musculoskeletal diseases, and the interventions' effect on long-term disability was excluded from the research.

De Boer et al. (2004) examined an occupational health intervention program for employees that had been screened as facing risk for long-term disability in terms of early retirement. A randomized controlled trial was constructed, assigning a group of over 50-year-olds who doubted their own work abilities either to an intervention group (n = 61) or to a control group (n = 55). The intervention program lasted for six months, after which the individuals were followed for two years. After the follow-up time, only 11 percent of the intervention group had been granted disability pensions (28 percent of the control group), and the individuals of the intervention group had had on average 82,3 sickness absence days in two years, which was 24 percent less than in the control group (107,8 days). De Boer et al. (2004) therefore conclude that occupational health interventions targeted to over 50-year-olds with a disability risk effectively reduce long-term disability.

To summarize, the previous research shows evidence of positive cost-effectiveness of disability preventing actions targeted at employees with identified disability risks. However, a comprehensive benefit-cost analysis of both short-term and long-term disability prevention with a societal perspective has not been previously conducted. This study aims to fill this gap and fulfill the previous research with a more economic perspective, to help employers and the society conduct economic decisions that increase the long-term welfare and wellbeing in the society.

Chapter 3

Institutional setting

This chapter presents the institutional setting relevant for the present study. To understand how the costs and benefits of disability prevention incur, the mechanisms of the Finnish sickness absence system and the Finnish disability benefit system are introduced in the section 3.1. The section 3.2 describes how employers and occupational health care service providers cooperate in disability prevention and organize targeted occupational health interventions.

3.1 Costs of disability

Disability imposes both direct and indirect costs to the society, and short-term disability and long-term disability impose costs through different mechanisms. The indirect costs can be frictional costs resulting from for example reorganization at worksites, or missed tax income. The direct costs vary by country depending on the legislation on sickness absences and the disability benefit system. The research setting of the present study took place in Finland and therefore the Finnish sickness absence practicalities and the Finnish disability benefit system are introduced in this section.

Employees in Finland are granted paid sick leave when they face short-term disability due to sickness or injury. The practicalities of granting the sick leave and paying the first sick leave day vary between industries and employers. Typically employees can stay home without a medical certificate for short sick leaves (1 to 3 days) and for longer sick leaves, the employers require a medical certificate. Typically the employers carry the first ten days of the sick pay of an uninterrupted sickness absence period. After this the employer or the employee - depending on the contract - may apply for a sickness allowance or rehabilitation allowance that can be granted for a maximum of 300 days. 300 days of sickness allowance is counted on the basis of a 6-day working week, so the period of the allowance may last altogether 350 days. The sickness allowance is paid by the Finnish national Social Insurance Institution (SII). SII pays the sickness allowance to the employer as long as the employer pays the sick pay for the employee. If the contract between the employer and the employee does not include sick pay, the sickness allowance is paid straight to the employee.

Short-term disability imposes indirect frictional costs on top of the employees' sick pays. The employers lose the added value from the potential work inputs. Additionally, the employers need to reorganize work shifts, schedules and responsibilities. In worst cases, sanctions are imposed on the employer for unfinished work or delays. The Confederation fo the Finnish Industries EK has estimated that in Finland the indirect sickness absence costs are on average twice as high as the direct sickness absence costs (Kaukinen & Saukkonen 2009).

In Finland persons aged from 16 to 64 may be granted a disability benefit when a sickness or injury has lasted around one year and the sickness allowance has been used. The disability benefit can be granted as a disability pension until further notice or as a temporary rehabilitation benefit for a fixed period of time. The benefit can be granted as full disability benefit or as partial disability benefit. The table 3.1 summarizes the disability benefit types that can be granted in the Finnish disability benefit system.

SII or an authorized pension provider such as a pension insurance company determines the disability benefit that the applicant will be or will not be granted. If doctors estimate that the person's sickness or injury cannot be cured such that the person has the ability to return to work, a disability pension will be granted if the expert named at the pension insurance agree with the attending doctors' assessment. If the doctors estimate that the person's capability to work is lower than 40% (scale 0 to 100%), full disability pension will be granted. If doctors estimate that the person's capability to work is lower than 40% (scale 0 to 100%), a partial disability pension will be granted. The monthly payment of partial disability benefit equals 50% of the monthly payment of full disability benefit.

If doctors estimate that a person has the ability to return to work with the help of rehabilitation or by changing profession, a temporary rehabilitation benefit will be granted instead of disability pension. The monthly payment of full rehabilitation benefit equals the monthly payment of full disability pension. Payments of partial benefits are equal to each other as well. If the person's work ability is not improved during rehabilitation, the person may be entitled to a disability pension. The disability pension turns into retirement pension when a person reaches 65 years. If the person was born before the year 1962, the retirement age lies between 63 and 65.

The pension contributions of each employee are determined by the already accrued pensions, and the pension earnings accumulation of future time that is estimated based on the employee's earnings during the five latest years and the time to retirement. Disability pension contributions are calculated by:

Table 3.1: Disability benefit types.

Disability benefit type	**Degree of working capacity**	**Pension duration**
Full disability pension	Lower than 40%	Until further notice
Partial disability pension	Lower than 60%, higher than 40%	Until further notice
Full rehabilitation benefit	Lower than 40%	Temporary
Partial rehabilitation benefit	Lower than 60%, higher than 40%	Temporary

$$\begin{aligned}\text{Monthly disability pension} = \{&(\text{Accrued pension earnings} + \\ &\text{future pension earnings})\times \\ &\text{Life expectancy coefficient}\},\end{aligned} \tag{3.1}$$

where

$$\begin{aligned}\text{Accrued pension earnings} = \{&\text{Cumulative earnings from the age of 17} \\ &\text{to date } \times 1,5\% \div 12\}\end{aligned} \tag{3.2}$$

and

$$
\begin{aligned}
\text{Future pension earnings} = \{&\text{Average annual earnings during the 5 latest} \\
&\text{full years } \times 1,5\% \div 12 \times \\
&\text{months until retirement } \div 12\}.
\end{aligned}
\tag{3.3}
$$

The life expectancy coefficient is issued by the Ministry of Social Affairs and Health to adjust the pension payments according to the life expectancy. The life expectancy coefficient reduces the monthly disability pension such that the expected cumulative disability payments remain constant as the life expectancy increases. The purpose of the life expectancy coefficient is to limit the growth of pension payments.

Full disability benefits are issued and paid by the pension insurance companies or, when a person's earnings have been especially low, SII, or both. Partial disability benefits are always paid by the pension insurance companies. The pensions paid by SII are financed from tax assets and mainly concern persons who have not been able to accumulate pension. Pension insurance companies finance the payments through the employers' and employees' work pension insurance payments (TyEL payments) and investment income. The amount of an employee's monthly TyEL payment is a fixed 7,5% proportion of the employee's salary. The amount of an employers' TyEL payments depend on the size of the company and the proportion of the company's employees who have been granted disability benefits during the last two years. The payments of the company are the higher the more disability benefits have been granted for the employees.

On top of the direct disability benefit costs, long-term disability imposes indirect costs as well. The indirect frictional costs at worksites consist of reorganization costs, decreases in productivity, and recruitment costs. Disability can also indirectly affect on customer satisfaction and employer image (Pekka 2017). The society also loses tax income when a person moves from a tax payer to a recipient of disability benefits. The frictional costs at the worksites and the missed tax income can be considered as high as the direct disability benefit costs that result to the society.

3.2 Disability prevention

Finnish employers, occupational health care service providers and pension insurance companies cooperate to prevent disability. Different programs exist to promote employees' ability to work depending on the employer. The programs include for example personnel surveys or health surveys, health interventions, or trainings for managers or employees.

Employers use health surveys to build an overview of the personnel well-being and to be able to target disability preventing actions to employees who face a high risk for disability. The surveys typically include self-assessive questions that scan the employees' mental and physical health. The disability risks are typically estimated based on the answers and the employees' previous sickness absence behavior. Based on the answers, the number of work disability risk factors are estimated for each employee to prioritize the employees based on their risks for long-term disability.

Targeted occupational health interventions represent a process where the employees' disability risks are first estimated with a help of a health surveys and then the employees who face a high risk for disability are invited to a health check. The occupational health care service provider plans and tailors the health checks in advance according to a the risk analysis of an employee. During the health check, the occupational health care service provider and the employee agree on a personal health plan to support the employee's ability to work.

The health surveys are typically financed by the employer but the employer's pension insurance company may subsidize the surveys or they may be included to the contract between the employer and the occupational health care service provider. The occupational health care services are financed by the employer and provided by the occupational health care service provider that in Finland is typically a private firm. Some of the occupational health care services are subsidized by SII.

Chapter 4

Methodology

As Hoch et al. (2002) state, economic evaluation in health economic research is often considered a branch "divorced on mainstream econometric techniques" and instead, "relying on statistical mainstream methods for clinical trials". In the present study I exploited various statistical methods to meet the research objectives and the requirements and constraints of the research setting. The framework of the present study combined the Average Treatment Effect and Net Benefits frameworks. The results of the framework were formed with Analysis of Covariance (ANCOVA). Missingness in the data was managed with Multivariate Imputation by Chained Equations (MICE). The salaries of the employees were predicted with polynomial regression. The impact of a possible selection bias that may occur due to an observational research setting was managed with propensity scores and Inverse Probability Weighting (IPW). The methods and frameworks that will be introduced in this chapter in more detail are the treatment effect and the net benefit frameworks, propensity scores, IPW, and MICE.

4.1 Treatment effect

In the present study the interest was to estimate the effect of a treatment on the net benefits of the prevention of short-term and long-term disability. Therefore treatment effect framework was used in the present study. Austin (2011) introduces the potential outcomes framework that assesses treatment effect on a sample of subjects. The framework includes two possible treatments: active treatment and control treatment, and an outcome. Each subject receives either active treatment or control treatment. Let Z indicate the treatment received, and Y the outcome. For active treatment $Z = 1$, and for control treatment $Z = 0$. Two possible outcomes for a subject i are $Y_i(1)$ for active treatment and $Y_i(0)$ for control treatment. Each subjects receives only one type of treatment. Therefore, we observe the outcome Y_i for each subject based on the actual treatment Z_i received. The Y_i actually observed is $Y_i = Z_i Y_{i,1} + (1 - Z_i)Y_{i,0}$. (Austin 2011)

At an individual level, the treatment effect for each subject is defined by $Y_i(1) - Y_i(0)$. At the population level, the average treatment effect (ATE) is defined by $E[Y_i(1) - Y_i(0)]$. When the given sample is representative of the population, the average treatment effect implicates the average effect of actively treating the entire population. (Austin 2011) Another measure for estimating treatment effect is the Average Treatment effect for the Treated (ATT), which represents the average treatment effect for the treated subjects (Imbens 2004). The ATT is defined by $E[Y(1) - Y(0)]|Z = 1$. When the actively treated subjects do not systematically differ from the controlled subjects, ATT = ATE.

4.2 Treatment effect estimation in observational studies

In Randomized Controlled Trials (RTCs), each subject is randomly assigned to a treatment group or a control group to receive either active treatment or control treatment. As a result, an unbiased estimate of the ATE can be directly determined from the research data, defined by $E[Y_i(1) - Y_i(0)] = E[Y_i(1)] - E[Y_i(0)]$. Unbiasedness of the research data allows researchers a less complicated process to draw conclusions from the data compared to biased data. Due to randomization the actively treated population and the controlled population do not on average systematically differ from each other.

Thus ATT = ATE in case of RCTs. (Austin 2011)

Because RCTs enable collecting unbiased data, one would prefer to build experimental studies or trials that assign the subjects to the treatment group and the control group by randomization. In practice, randomization is not always possible in experimental studies. Epidemiological and other experimental studies that aim to assess a treatment effect are often constructed with observational data (Lunceford Jared K. & Davidian Marie 2004). However, observational data can be considered biased because treatment exposure in observational studies is typically not assigned by randomization.

An observational study has been defined as an empirical investigation to assess cause-and-effect relationships in a setting in which using controlled experimentations is not feasible (Cochran & Chambers 1965). Therefore the treatment assignment of a subject in observational studies may be associated with covariates that are also associated with the subject's potential response. When the exposure to treatment is associated with subject characteristics, the research setting can be considered biased (Cochran & Chambers 1965). Estimation of treatment effects in observational studies is complicated because actively treated subjects may differ significantly from untreated subjects and one cannot draw direct unbiased estimates from observational data: $E[Y(1)|Z=1] \neq E[Y(1)]$, and $ATT \neq ATE$.

Due to reasons above researchers always aim to minimize the impact of bias in the research data by designing the research setting or with different statistical methods such as propensity scores and Inverse Probability Weighting (Austin 2011) (Lunceford Jared K. & Davidian Marie 2004). The data used in the present study was observational and therefore such methods were used in the present study to minimize the impact of possible selection bias in the samples of subjects.

4.3 Propensity scores

Propensity score and propensity score methods allow one to reduce the impact of bias in estimating the average treatment effect from observational data. The propensity score was first introduced by Rosenbaum and Rubin (1983) as a score to balance the treatment group and the control group of subjects such that the baseline characteristics of the subjects are taken into account. The propensity score e_i is the probability of treatment assignment conditional on the baseline characteristics, or more precisely, on the observed baseline covariates: $e_i = Pr(Z_i = 1|X_i)$. Subjects that have a similar propensity score have similar baseline covariates regardless of the treatment assignment. (Rosenbaum & Rubin 1983)

Rosenbaum and Rubin (1983) stated two sufficiency conditions to estimate propensity scores to obtain unbiased estimates of average treatment effects: a) $(Y(1), Y(0)) \perp Z|X$, and b) $0 < Pr(Z_i = 1|X_i) < 1$. The first condition states that treatment assignment is independent of potential outcomes conditional on the observed baseline covariates. The second condition states that each subject has a nonzero probability for each treatment. When these conditions hold, treatment assignment is strongly ignorable and estimated propensity scores enables one to obtain unbiased estimates of average treatment effects. (Rosenbaum & Rubin 1983)

Previous studies suggest that the covariates for the propensity scores should be chosen based on their association with both treatment and outcome (Harder, Stuart & Anthony 2010) (Brookhart, Schneeweiss, Rothman, Glynn, Avorn & Stürmer 2006). The decisions should be made by measuring the variables that explain receiving the treatment and the outcome at the baseline. Only fixed variables and variables that describe a subject's behavior or condition before the treatment - not after the treatment - should be included in the covariates to avoid the results to be affected by the treatment (Harder et al. 2010).

The propensity score can be determined for both randomized and non-randomized experiments. For RCTs, the true propensity score is naturally known due to controlled randomization. For observational studies, the propensity score is not known but can be estimated. In practice, the propensity score is most often estimated using a logistic regression model in which treatment status is regressed on the observed covariates (Austin 2011) (Brookhart et al. 2006). The estimated propensity score is the predicted probability of treatment derived from the fitted regression model (Austin 2011).

4.4 Inverse probability weighting

Inverse probability weighting (IPW) introduced by Rosenbaum (1987) is a methods that creates a sample of population by using weights based on the propensity score (Austin 2011). Each subject's weight is equal to the inverse probability of receiving the treatment (active or control) that the subject actually received. Further, propensity scores and IPW enable estimating treatment effects because with IPWs, treated and untreated subjects can be compared to each other. The method for weighting depend on whether the interest is to estimate ATE or ATT.

When the interest is to estimate the ATE, the weights can be defined by $w_{i,ATE} = Z_i/e_i + (1 - Z_i)/(1 - e_i)$, where Zi is the subject i's actual treatment assignment observed and e_i is the propensity score for subject i. The estimate for ATE is $1/n \sum(Z_iY_i/e_i) - 1/n \sum((1-Z_i)Y_i/(1-e_i))$, where n is the number of subjects. (Austin 2011) (Lunceford Jared K. & Davidian Marie 2004)

When the interest is to estimate ATT, the weights for the actively treated can be calculated by $w_{i,ATT} = Z_i + (1 - Z_i)e_i/(1 - e_i)$. The weights for estimating ATC, average treatment effect for subjects that have received control treatment, can be calculated by $w_{i,ATC} = Z_i(1-e_i)/e_i$. (Austin 2011)

When utilizing the weights introduced, one will be able to generate comparable samples of the treated and untreated subjects such that the outcome of each subject observed will be taken into account in the analysis. IPW therefore allows to create samples where all observed subjects have a higher probability to be taken into account when compared to Propensity Score Matching where individual subjects with similar propensity scores are compared to each other without weighting (Austin & Schuster 2016) (Austin 2011). For example, let a sample where one treated subject and multiple untreated subjects have similar propensity scores. With Propensity Score Matching, one treated subject will be compared to one untreated subject with a similar propensity score and all the other untreated subjects with the same propensity scores will be excluded from the analysis. With IPWs, the treated subject can be compared to all untreated subjects at the same time. The treated and untreated samples become comparable because IPWs weigh the subjects such that the sum of the weights of the treated subjects will be equal to the sum of the weights of the untreated subjects with similar propensity scores.

The performance of IPW can be verified by analyzing the balance of the variables of interest between the treatment and the comparison groups. A common measure used is the standardized bias, Standard Mean Difference (SMD) which describes the difference in the mean covariate value divided by the standard deviation of the treated group (Harder et al. 2010) (Ho, Imai, King & Stuart 2007). According to Ho et al. (2007), the difference between the groups is acceptable if the SMDs between the groups regarding the propensity score covariates are less than 0.25.

4.5 Benefit-cost analyses

This study examined targeted occupational health interventions' treatment effect as a benefit-cost analysis. Benefit-cost analyses or cost-benefit analyses are used in health economic studies where the interest is to analyze cost-effectiveness in monetary terms (Johannesson & Jönsson 1991). Analyzing the costs and benefits in the same units increases the ability to judge if investment decisions are desirable (Johannesson & Jönsson 1991). Johannesson and Jönsson (1991) link the theory base of cost-benefit analyses to the economic welfare theory and the concept of consumer surplus.

In practice benefit-cost analyses are typically conducted by analyzing benefit-cost ratios or net benefits. Benefit-cost ratios (B/C) tell how many euros are saved for every euro spent. Such rhetoric can however be misleading because benefit-cost ratios may not be constant when the costs change, and higher ratios can be easily achieved by manipulating costs. Net benefit (B-C) is another benefit-cost indicator that communicates the nominal difference between the benefits and the costs. Net benefits are less easy to be manipulated, and the scale of the benefits achieved can be considered easier to be understood (Stinnett & Mullahy 1998). Therefore, net benefits were used in the present study as the framework to describe the difference of the benefits and costs resulted from the treatment. The framework used in the empirical analysis that combines the Average Treatment effect for the Treated and Net Benefits will be described in more detail in the section 5.6.

4.6 Multivariate imputation by chained equations

The data used in the present study included some missingness in the health survey answers, and this limitation was solved with multiple imputation.

Different imputation methods exist for dealing with missing data. Missingness of data can be problematic for data analysis when the missingness is systematic instead of random, which can lead to biased estimations if only complete cases are used for data analysis (Little & Rubin 2019) (Azur, Stuart, Frangakis & Leaf 2011). Imputation methods aim to solve this problem by filling the gaps in e.g. survey data where some individuals have not responded to all parts of the survey. Missing data can be especially crucial in observational studies where propensity scores and IPW are used (Leyrat, Seaman, White, Douglas, Smeeth, Kim, Resche-Rigon, Carpenter & Williamson 2019) (Eulenburg, Suling, Neuser, Reuss, Canzler, Fehm, Luyten, Hellriegel, Woelber & Mahner 2016).

Imputation methods can be divided to single imputation methods and multiple imputation methods based on the number of imputed datasets the imputation algorithms create. As Azur et al. (2011) synthesize, single imputation methods such as mean imputation are simpler but they do not account the uncertainty of the values imputed in the data analysis. Multiple imputation methods have a number of advantages compared to single imputation because these methods create multiple predictions for the missing values, and therefore the data analyses take into account the uncertainty of the imputations, yielding to more accurate standard errors.

Multivariate Imputation by Chained Equations (MICE) is a multiple imputation method that takes into account the existing values of the individual that has missing values in the dataset (Azur et al. 2011) (Buuren & Groothuis-Oudshoorn 2011) (Buuren & Groothuis-Oudshoorn 2010). The missing values are filled based on the observed values for a given individual and the related values observed for other participants in the dataset. On top of accounting for the statistical uncertainty in the imputations, MICE can take into account variables of different data types as well as patterns of the missing data. Previous studies (e.g. Eulenburg et al. 2016) have applied propensity scores and IPW after MICE with observational retrospective data.

The chained equations is a process for imputing the data. The table 4.1 introduces the chained equations process in 6 general steps of MICE as described by Azur et al. (2011). The imputation process (Steps 1-6) is repeated to create multiple imputed datasets where the observed data is equal and the originally missing data differs. The steps 1 to 6 generate one imputed dataset. Increasing the number of imputed datasets increases the feasibleness of the analyses but computing the imputation algorithms may last for hours. Typically 5 to 10 datasets can be considered sufficient (Eulenburg et al. 2016) (Azur et al. 2011).

After the MICE procedure, each dataset is complete so that the data analysis can be conducted on them. The data analysis is conducted to all imputed datasets separately after which the results of the imputed datasets are pooled together (Azur et al. 2011).

Table 4.1: The general steps of MICE. (Azur et al., 2011)

Step	Description
Step 1	A simple imputation, such as imputing the mean, is performed for every missing value in the dataset. These mean imputations can be thought of as "place holders".
Step 2	The "place holder" mean imputations for one variable ("var") are set back to missing.
Step 3	The observed values from the variable "var" in Step 2 are regressed on the other variables in the imputation model, which may or may not consist of all of the variables in the dataset. In other words, "var" is the dependent variable in a regression model and all the other variables are independent variables in the regression model. These regression models operate under the same assumptions that one would make when performing (e.g.,) linear, logistic, or Poison regression models outside of the context of imputing missing data.
Step 4	The missing values for "var" are then replaced with predictions (imputations) from the regression model. When "var" is subsequently used as an independent variable in the regress
Step 5	Steps 2–4 are then repeated for each variable that has missing data. The cycling through each of the variables constitutes one iteration or "cycle". At the end of one cycle all of the missing values have been replaced with predictions from regressions that reflect the relationships observed in the data.
Step 6	Steps 2 through 4 are repeated for a number of cycles, with the imputations being updated at each cycle. The number of cycles to be performed can be specified by the researcher. At the end of these cycles the final imputations are retained, resulting in one imputed dataset.

Chapter 5

Data and models

5.1 Data sources and collection

This study was conducted as a retrospective review of prospectively collected register data. The data of the present study combined register data from multiple personal data registers that included the patient register and the occupational personnel health survey register of Terveystalo Oyj, the largest private health care corporation and occupational health care service provider in Finland, and data from the pension data register of the Finnish Centre for Pensions. The data was collected between the years 2009 and 2016. In addition to the personal data registers, the study exploited statistical average salary data from Statistics Finland.

The data utilized in the present study consisted of 3 datasets. The con-

Table 5.1: Summary of the datasets.

Dataset	Contents
Dataset A	Employees' demographic information, health survey answers and results, health check behavior within 12 months after the survey and employees' disability-related behavior during the follow-up period.
Dataset B	The health care services used by employees 12 months before and after the health survey, and their costs.
Dataset C	Finnish average salaries by age groups, sexes, occupational statuses and industries 2016.

tents of the datasets have been summarized in the table 5.1.

The dataset A contained the personnel health survey responses and results, the sickness absence data and the granted disability benefits of 22,136 employees that had during the data collection period been working at companies that had outsourced the occupational health care services for Terveystalo. The health surveys were collected between the years 2012 and 2015, and the follow-up lasted until the end of 2016. The dataset A was filtered to contain only the employees of interest in the analysis. Employees who had retired or changed the employer so that the follow-up period was not complete were excluded. I also removed the employees who already had been granted some disability benefits and those who had had at least 100 sick leave days during the year before the survey because they had been directed to a workability-related health intervention process regardless of the survey. After the eliminations, the dataset A contained 20,462 employees. The sample of subjects represented employees from multiple industries, ages, sexes, and occupational statuses. The table 5.2 describes the metadata and the frequency distributions of the employees' demographic information.

All employees in the sample had conducted a self-evaluating health survey. Based on the answers the number of work disability risk factors of each employee had been analyzed and the the employees had been assigned to a risk group that indicated the employees' risk for disability. The criterion for the highest risk rate had been the work disability risk factor (WD) that indicated the number of chronic conditions that predict disability. The employees that had reported of symptoms of at least one work disability risk factor (WD>0) had been assigned into the highest disability risk group, and the employees without identified work disability risk factors (WD=0) were assigned into lower disability risk groups. Especially those employees who reported problems with future working ability, i.e. pain and impairment due to musculoskeletal problems, insufficient sleep, stress or fatigue, or depression symptoms, were assigned into the high risk group. The table 5.3 describes the metadata and the frequency distributions of the employees' work disability risk factors. The dataset also included more results of the health surveys (e.g. BMI, alcohol consumption, problems with hearing) but due to the high number of variables the frequency distributions show only the most relevant ones that were defined as work disability risk factors.

The contract between the occupational health service provider and the employer determined which employees were invited to the survey-driven health check. The health checks were been planned and customized for each employee to take the employee's state of health into account. The occupational health care service provider had invited all employees with the highest risk rate to attend a health check regardless of the employer. The occupational health service provider may have sent invitations to employees with lower risk rates as well depending on the scope of the service contract. Targeted occupational health interventions, however, were expected to provide the highest effectiveness on employees with higher disability risks. All high-risk employees did not attend the targeted health intervention despite the invitation. Employers and occupational health care service providers can promote health interventions but cannot compel the employees to attend them. Therefore some but not all reacted to the invitation and attended the health check and received treatment. The remaining employees who did not attend the health check can be considered non-treated subjects. The table 5.4 describes the metadata and the frequency distributions of the employees' health check behavior within 12 months after the health survey.

The dataset A also included data of the employees' disability related behavior. The number of sickness absence days and sickness absence workdays 12 months before and after the survey represented an employee's short-term disability before and after the survey. The follow-up period length for short-term disability was in the present study therefore equal to the follow-up period length in previous research of e.g. Taimela et al. (2007). The dataset also included information whether the employees had been granted disability benefits during the follow-up period. The table 5.5 shows the frequency distributions of the employees' short-term disability related behavior during the 12-month follow-up periods, and the table 5.6 describes the metadata and the frequency distributions of the employees' long-term disability related behavior during the full follow-up period.

The dataset B included all health services that the employees in the dataset A had attended at Terveystalo 12 months before and after filling the health survey. The dataset included the cost of each service per employee and information if the services had been subsidized by SII. The table 5.7 describes the frequency distributions of the employees' health care utilization costs during the 12-month follow-up periods.

The dataset C was the statistical data of average salaries per industry, sex, age and occupational status group provided by Statistics Finland. Since the datasets A and B did not include salary data and the disability benefit costs per employee, this public data was utilized to predict the expected sickness absence cost and the expected disability benefit cost of each individual in the dataset A. The subsection 5.4.2 will describe the process and the predictions in more detail.

Table 5.2: Metadata and frequency distributions of the employees' demographic information.

Variable	Values	N	%
Age (at survey date)	Continuous variable; One-digit decimal number Min: 19.1; Median: 46.0; Max: 68.0		
Sex	1 Male	8,592	42
	2 Female	11,870	58
Occupation	1 Blue collar worker	6,132	30
	2 White collar worker	11,300	55
	3 Manager	3,030	15
Industry	A Agriculture, forestry and fisheries	0	0
	B Mining and quarrying	3	0
	C Industrial	1,882	9.2
	D Electricity, gas and heat supply, refrigeration	304	1.5
	E Water supply, sewage and waste water treatment, waste management and other environmental clean-up	297	1.5
	F Construction	544	2.7
	G Wholesale and retail trade	3,344	16.3
	H Transport and storage	395	1.9
	I Accommodation and catering activities	1,567	7.6
	J Information and communication	561	2.7
	K Financing and insurance business	338	1.7
	L Real estate activities	83	0.4
	M Professional, scientific and technical activities	1,372	6.7
	N Administrative and support services	210	1.0
	O Public administration and defense	4,244	20.7
	P Training	2,757	13.5
	Q Health and social services	1,400	6.8
	R Art, entertainment and recreation	357	1.7
	S Other service activities	420	2.0
	X The industry is unknown	384	1.9

Table 5.3: Metadata and freaquency distributions of the employees' work disability risk factors.

Variable	Values	N	%
WD (No. of work disability risk factors)	0	15,346	75
	1	3,445	17
	2	1,1125	5
	3	390	2
	4	116	1
	5	40	0
Depressive.Symptoms	Green	17,401	85
	Yellow	2,141	10
	Red	920	4
Pain.and.Physical.Impairment	Green	13,370	65
	Yellow	4,618	23
	Red	2,474	12
Sleep.and.Alertness	Green	14,204	69
	Yellow	4,426	22
	Red	1,832	9
Wellbeing.at.Work	Green	16,769	82
	Yellow	3,046	15
	Red	647	3
Work.Ability.Prognosis	Green	18,769	92
	Yellow	0	0
	Red	1,693	8

Green = No risk
Yellow = Small risk
Red = Significant risk

Table 5.4: Metadata and frequency distributions of the employees' health check behavior.

Variable	Values	N	%
Health check	No	12,381	61
	Yes	8,081	39
Health check type, 0 to 6 months after survey	Targeted health check	3,533	17
	Traditional health check	2,818	14
Health check type, 6 to 12 months after survey	Targeted health check	659	3
	Traditional health check	1,071	5

Table 5.5: Frequency distributions of the employees' short-term disability data.

Variable	Min	1st Quarter	Median	3rd Quarter	Max
Sick.Leave.Days.Before	0	0	0	5	99
Sick.Leave.Workdays.Before	0	0	0	5	75
Sick.Leave.Days.After	0	0	1	6	359
Sick.Leave.Workdays.After	0	0	1	5	256

Table 5.6: Metadata and frequency distributions of the employees' long-term disability data.

Variable	Values	N	%
Disability.Benefit	Yes	139	0.7
	No	20323	99.3
Full.Disability.Pension	Yes	40	0.2
	No	20422	99.8
Part.Disability.Pension	Yes	48	0.2
	No	20414	99.8
Full.Rehab.Benefit	Yes	34	0.2
	No	20428	99.8
Part.Rehab.Benefit	Yes	19	0.1
	No	20443	99.9

Table 5.7: Frequency distributions of the employees' survey and health care utilization costs.

Variable	Min	1st Quarter	Median	3rd Quarter	Max
Survey.Costs	15.50	15.50	15.50	15.50	15.50
Healthcare.Costs.Before	0.00	0.00	00.00	0.00	6,220.23
Healthcare.Costs.After	0.00	0.00	00.00	23.07	5,834.66

5.2 Ethical considerations

This study was a part of a larger research project that had received permission from the ethic committee of Pirkanmaa health care region (Pirkanmaan sairaanhoitopiiri) in spring 2016.

The register data used in the present study includes sensitive information. National Institute for Health and Welfare of Finland had granted permission to exploit and combine the data from the different data registers.

The patient data had included identifiable information only when it was combined with the pension data of the Finnish Centre for Pensions. After the combination, the data was pseudonymized. The combination and pseudonymization of the data was executed in University of Tampere. All analyses formulated in the present study were conducted with entirely pseudonymous data.

5.3 Limitations of the data

The data included in the present study was observational and therefore had the possibility to include selection bias because the allocation of employees in treated and non-treated groups had not been randomized - the employees had been able to choose whether to participate to the intervention or not. The employees who had not attended the health check may had not felt as ill as those who had attended the health check despite similar responses in the survey. To mimic a controlled research setting, propensity scores and Inverse Probability Weighting (IPW) were used in the empirical analysis of the present study. The methods enabled assembling reasonably comparable groups from the data, a treatment group and a control group, such that as unbiased as possible estimators were able to be predicted from the data.

The data also included some missingness in the employees' health survey answers. The table 5.8 lists the number of missing values per each variable that had missing values. Missingness in general causes limitations to research but in case of the present study, the missingness could be considered a minor issue that was eliminated with imputation methods. In the present study missingness caused limitations to the performance of IPW because the standardized biases of some variables were higher than the 0.25 limit with the complete cases dataset. This challenge was solved with MICE: with the imputed datasets, standardized biases became acceptable.

Another limitation was that the actual salary data and the costs of the potential disability benefits per employee were not included in the datasets. This limitation was solved by utilizing the publicly available average salary data of different industries, occupational statuses, sexes and ages. The expected salary data for each employee was predicted based on the external data, and each individual's sickness absence day costs and disability benefit

Table 5.8: Missing values in the dataset A

Variable	Missing values, n	%
Alcohol.Consumption	5,209	25
BMI	240	1
Depressive.Symptoms	28	0
Diabetes.Risk	474	2
Occupation	76	0
Pain.and.Physical.Impairment	34	0
Physical.Activity	31	0
Physical.Limitation.Work	5,584	27
Problems.with.Hearing	224	1
Problems.with.Vision	335	2
Sleep.and.Alertness	31	0
Smoking	148	1
Use.of.Intoxicants	162	1
Weight.Management	210	1
Wellbeing.at.Work	24	0
Work.Ability.Prognosis	78	0

N = 20,462

costs were derived from the predictions. The predicted salaries and costs of disability may differ from reality but on the other hand, the predicted values correspond to the average salaries and pensions of the Finnish population.

One limitation is that the exact timing of health checks or the timing of the health check invitations were not known. This is a limitation because it was known that the employees had been invited to the targeted occupational health intervention in a prioritized order. It was possible to distinguish those employees who had attended a health check within 6 months after the survey from those who had attended the health check between 6 and 12 months after the survey. The assumption was made that the employees that attended the health check within 6 months were on average invited to the survey before the others due to higher disability risk. It was however not possible to distinguish the untreated high-risk employees who had been invited to the health check within 6 months of those untreated high-risk employees who had received the invitation between 6 to 12 months after the survey. The impact of this limitation was tried to be minimized by including the work disability risk factors in the propensity score covariates.

5.4 Data analysis

5.4.1 Imputation and merging the datasets

I started the data processing with multivariate imputation (MICE) to predict missing values for the dataset A that contained the 20,462 employees of interest. I created 5 imputed datasets with 5 iterations with the MICE method as described in the section 4.6. Predictive Mean Matching was used as the imputation method with MICE.

I then joined the dataset B (health care utilization and cost data) into the imputed datasets and the original dataset without imputations.

5.4.2 Direct disability benefit and sickness absence cost prediction

I continued with predicting the salary data and the potential disability pension cost data from the dataset C for each employee with a second power polynomial regression model. Polynomial regression was chosen because the development of salaries by age in different occupational groups and industries followed a curve rather than a linear line. Second power polynomial regression was used for the quantitative variable age and linear regression was used for categorical variables.

As only part of the employees in the dataset A included the information about industry, two different models were created. The primary model was used as the primary model and the second model was used if the employee's industry was unknown. The the primary model included the age, the sex, the occupational status and the industry of each employee as predictors. The second model included the same predictors as the primary model except the industry. The primary model was used for the set of employees in the dataset A which had an industry defined (*"A"* to *"S"* as described in the table 5.2), and the secondary model was used for employees whose industry was defined as unknown (*"X"* as described in the table 5.2).

To present the models, I define k_S: number of levels in the category *sex*, k_O: number of levels in the category *occupation*, k_I: number of levels in the category *industry*. In the present study, $k_S = 2$, $k_O = 3$ and $k_I = 19$ (industries from *"A"* to *"S"*) as described in the table 5.2. To construct and fit the models, I converted the relevant variables of the datasets to binary indicator variables using a single reference level per category. This way I obtained $d_1 = 23$ variables in total, and $d_2 = 5$ when excluding the industries.

I denote observations with $\mathbf{x}^{(i,M)}$, where $i =$ the index of the observation, $M =$ the set of observations, 1 if the the industry of observation was known, 2 if not. Furthermore, I present the number of observations with and without industry information as n_1 and n_2 respectively. This way I can present a single observation with industry value as

$$\mathbf{x}^{(i,1)} = [x_a^{(i,1)}, x_a^{(i,1)2}, x_s^{(i,1)}, x_{o,1}^{(i,1)}, x_{o,2}^{(i,1)}, x_{i,1}^{(i,1)}, ..., x_{i,18}^{(i,1)}], i \in [0, n_1] \tag{5.1}$$

and a single observation without industry value as

$$\mathbf{x}^{(i,2)} = [x_a^{(i,2)}, x_a^{(i,2)2}, x_s^{(i,2)}, x_{o,1}^{(i,2)}, x_{o,2}^{(i,2)},], i \in [0, n_2] \tag{5.2}$$

I further present the sets of observations with matrices

$$\mathbf{X}_1 = \begin{bmatrix} \mathbf{x}^{(0,1)} \\ \mathbf{x}^{(2,1)} \\ \vdots \\ \mathbf{x}^{(n_1,1)} \end{bmatrix}, \mathbf{X}_1 \in \mathbb{R}^{n_1 \times d_1} \tag{5.3}$$

and

$$\mathbf{X}_2 = \begin{bmatrix} \mathbf{x}^{(0,2)} \\ \mathbf{x}^{(2,2)} \\ \vdots \\ \mathbf{x}^{(n_1,2)} \end{bmatrix}, \mathbf{X}_2 \in \mathbb{R}^{n_2 \times d_2} \tag{5.4}$$

Finally, I present the regression model for observations in $\mathbf{X}_1$ as:

$$y_1 = \alpha_1 + \boldsymbol{\beta}_1 \mathbf{X}_1^\top + \epsilon_1 \tag{5.5}$$

and for observations in $\mathbf{X}_2$ as:

$$y_2 = \alpha_2 + \boldsymbol{\beta}_2 \mathbf{X}_2^\top + \epsilon_2 \tag{5.6}$$

where $\boldsymbol{\beta_1} = [\beta_{0,1}, \beta_{1,1}, ..., \beta_{d_1,1}]$ and $\boldsymbol{\beta_2} = [\beta_{0,2}, \beta_{1,2}, ..., \beta_{d_2,1}]$.

When testing the fitted models, the p-values were less than 0.001 for both models and the R^2 was 0.853 for model y_1 and 0.753 for the model y_2, so I considered the models sufficient for the purpose. With the models, I predicted the salaries for all employees in the dataset A. Of the salaries predicted, I deduced the sick leave costs per each employee 12 months before and after the health survey and the disability benefit costs of all employees who were granted a disability pension or a rehabilitation benefit during the follow-up period. The direct cost of one sick leave workday was equal to an employee's predicted salary costs during that day, including the salary-related side expenses.

From the salary data, I calculated the expected monthly disability pension with the formulas presented in the section 3. I then estimated the net present value of the disability benefit costs until the end of the rehabilitation benefit or until the expected retirement age of the employee. If the employee was granted a rehabilitation benefit, the disability benefit costs were calculated for a fixed period of time. If the person received a disability pension, the

Table 5.9: Frequency distributions of the estimated direct costs of disability and related variables.

Variable	Min	1st Quarter	Median	3rd Quarter	Max
Salary.Month	893	2,720	3,274	4,000	5,404
Expected.Disability.Benefit. Cost.Month	595	2,262	2,313	2,757	3,765
Direct.Sick.Leave.Workday.Costs. Before	0	0	0.00	1,007	24,578
Direct.Sick.Leave.Workday.Costs. After	0	0	100	1,126	65,268
Direct.Disability.Benefit.Costs	0	0	0	0	555,212

costs of the benefits were calculated as the cumulative costs until the official retirement age of the individual. I used the average age of moving to labor force (18.69) (OSF 2019) and the official retirement age per year of birth (63 to 65) to estimate the length of the career and the expected time to retirement for each employee. I assumed the index adjustment for the pensions equal to the discount rate when calculating the net present value of the direct costs of moving from working life to receiving disability benefits.

The table 5.9 presents the frequency distributions of the estimated salaries, the expected monthly disability benefit payments, and the estimated direct costs of disability that were realized during the follow-up period.

5.4.3 The estimation of the PS and IPW

I chose the variables of interest for propensity score estimation and estimated the propensity scores for each employee as described in the section 4.3. With the propensity scores I formulated the IPWs for each employee as described in the section 4.4. The weights were calculated to estimate the Average Treatment Effect for the subjects in the treatment and control groups.

Variables for the PS were chosen based on their association with both treatment and outcome as recommended in the previous studies (Harder et al. 2010). The decisions were made by measuring the variables that explained receiving the treatment (attendance to a survey-based health check) and the outcome (net benefits, to be described in the section 5.6) at the baseline. I created and iterated models to test the relative effects of the variables that might associate with the treatment and outcome. I utilized only class variables (such as sex) and variables that describe an employee's behavior or condition before the treatment - not after the treatment - to avoid the results to be affected by the treatment. I repeated the procedure separately with the complete cases dataset and the imputed datasets as suggested in the MICE method.

The final confounding covariates selected in the model included demographics (Age, Sex), the socioeconomic status (Occupation, Industry), the number work disability risk factors (WD), BMI, alcohol consumption, diabetes diagnosis, the employee's own perception of well-being at work and health (Insufficient Job Control, Work Life Conflict, Strain Due to Rewarding, Lack of Social Support, Work Strain, Dissatisfaction, Depressive Symptoms, Physical Activity, Physical Limitation Work, Problems with Hearing, Problems with Vision, Self Reported General Diseases, Self Reported Symptoms, Sleep and Alertness), the sickness absense behavior within one year before the survey, and the health care utilization costs within one year before the survey. The year of the health survey was also selected as a propensity score covariate to balance the employees with different follow-up period lengths.

5.5 Treatment groups

In the analysis, the 20,462 employees in the dataset of interest were able to be assigned to a treatment groups based on the work disability risk factors found and the attendance to different health checks. All employees identified with at least one work disability risk factor had been invited to a targeted health check. Altogether 5,116 employees had been identified with at least one work disability risk factor. Some employers had invested to broader occupational health care services where employees without a remarkable disability risk had also been directed to a targeted health check. Some of the employees who did not attend a targeted health check attended a traditional non-targeted health check. Therefore the interest was to distinguish those employees who had been identified with a risk for disability in the analysis. Therefore the main analysis was restricted to employees with at least one work disability risk factor (WD>0). A separate sensitivity analysis was made on employees with no work disability risk factors (WD=0).

Different treatment groups were defined based on an employee's attendance to a health check. The treatment group 1_{H1} included those employees who attended to a targeted occupational health intervention within 6 months after filling a health survey. The comparison group $0_{H1,H2}$ included those employees who did not attend any health intervention within 12 months after filling the health survey. The comparison group 2_{H1} included those employees who attended a traditional, non-targeted health intervention (a traditional health check that is arranged at fixed time intervals) within 6 months after filling the health survey. The treatment group 1_{H2} included those employees who attended a targeted occupational health intervention between 6 and 12 months after filling a health survey. The comparison group 2_{H2} included those employees who attended a traditional, non-targeted health intervention between 6 and 12 months after filling the health survey. The table 5.10 summarizes the number of employees by treatment groups.

Table 5.10: The number of employees by treatment groups

Treatment group	**WD >0**	**WD = 0**	**Total**
$0_{H1,H2}$	2,107	10,274	12,381
1_{H1}	1,679	1,854	3,533
2_{H1}	831	1,987	2,818
1_{H2}	284	375	659
2_{H2}	215	856	1,071
Total	**5,116**	**15,346**	**20,462**

The main treatment group of interest was $1_{H1,WD>0}$ because these employees were identified with a risk for disability and attended to a targeted occupational health intervention within 6 months after the health survey. This group was compared with the group $0_{H1,H2;WD>0}$ where the employees did not attend any health check to receive the benefit-costs of targeted occupational health interventions compared to no intervention.

For sensitivity analysis, the treatment group $1_{H1,WD=0}$ was compared with $0_{H1,H2,WD=0}$ to see if the disability risk level of an employee was relevant in estimating the net benefits of targeted occupational health interventions. Another sensitivity analysis was made with the treatment group $1_{H2,WD>0}$ and $0_{H1,H2;WD>0}$ to see if the timing of a targeted occupational health intervention affected the net benefits. As can be seen from the table 5.10, 86 percent of targeted health checks were conducted within 6 months after filling the survey. It was expected that faster and more proactive treatment provides higher effectiveness on the net benefits. All pairs of treatment and comparison groups were separately balanced with IPW to reduce the possible selection bias included in the research setting.

A sensitivity analysis would have been interesting between the treatment groups 2_{H1} and 1_{H1} or $0_{H1,H2}$ as well but this was not conducted due to low reliability of the doctors' markings related to the treatment group 2_{H1} and 2_{H2}. According to Terveystalo, some of the employees marked with a traditional health check actually attended a targeted, survey-based health check but the doctors did not mark them correctly. This can also be inferred from the table 5.10: the size of the group 2_{H1} is larger than the group 2_{H2}. The relative difference is significantly wider than the difference between the groups 1_{H1} and 1_{H2}. Especially the group $2_{H1,WD>0}$ is highly likely to include employees who attended a targeted health intervention. It was unfortunately impossible to ascertain the correct health check type of these employees afterwards. The markings of the employees in the groups 1_{H1}, 1_{H2} and $0_{H1,H2}$ were consistent and the data analysis was able to be reasonably reliably conducted with these treatment groups.

The table 5.11 presents the performance of PS and IPW in reducing possible selection bias between the main treatment group $1_{H1,WD>0}$ and the main control group $0_{H1,H2;WD>0}$. The sensitivity analysis I was conducted with the same treatment groups as the main analysis. The table 5.12 presents the performance of PS and IPW in reducing possible selection bias between the treatment group $1_{H2,WD>0}$ and the control group $0_{H1,H2;WD>0}$ of the sensitivity analysis II. The table 5.13 presents the performance of PS and IPW in reducing possible selection bias between the treatment group $1_{H2,WD=0}$ and the control group $0_{H1,H2;WD=0}$ of the sensitivity analysis III. As the tables show, most of the possible selection bias was successfully eliminated from the data with IPW for the imputed datasets (SMDs < 0.25). The differences regarding especially the demographic background variables (industry, sex, occupation) and the number of work disability risk factors (WD) were more sufficiently balanced with the imputed datasets. The IPW procedure was especially successful between the treatment groups of the main analysis with the imputed datasets (SMDs < 0.1). The performance was not as effective for the groups constructed from the complete cases datasets. Therefore the data analysis to answer the main research question was conducted with the imputed datasets, and the results were pooled together as suggested in the MICE method.

Table 5.11: Standard Mean Differences of propensity score covariates between treatment group $1_{H1,WD>0}$ and control group $0_{H1,H2;WD>0}$ by datasets.

	Complete cases	Imputed datasets, min	Imputed datasets, mean	Imputed datasets, max
Age	0.186	0.003	0.004	0.006
Sex	0.170	0.002	0.004	0.006
Occupation	0.235	0.041	0.048	0.058
Industry	0.592	0.022	0.027	0.032
Q.Year	0.083	0.006	0.008	0.013
DiabetesK	0.061	0.009	0.021	0.037
WD	0.189	0.021	0.026	0.031
Insufficient.Job.Control	0.040	0.011	0.019	0.025
Work.Life.Conflict	0.004	0.006	0.015	0.022
Strain.Due.to.Rewarding	0.012	0.001	0.001	0.002
Lack.of.Social.Support	0.017	0.003	0.005	0.007
Dissatisfied	0.050	0.003	0.006	0.011
Any.Work.Problem	0.004	0.001	0.004	0.006
Alcohol.Consumption	<0.001	0.008	0.019	0.033
BMI	0.033	0.004	0.008	0.013
Depressive.Symptoms	0.121	0.014	0.018	0.023
Pain.and.Physical.Impairment	0.112	0.016	0.022	0.035
Physical.Activity	0.008	0.002	0.005	0.009
Physical.Limitation.Work	0.124	0.028	0.040	0.068
Problems.with.Hearing	0.097	0.012	0.016	0.020
Problems.with.Vision	0.173	0.005	0.013	0.021
Self.Reported.General.Diseases	0.072	0.003	0.009	0.013
Self.Reported.Symptoms	0.146	0.005	0.010	0.019
Sleep.and.Alertness	0.087	0.008	0.012	0.017
Sick.Leave.Days.Before	0.038	0.008	0.020	0.027
Healthcare.costs.before	0.070	0.010	0.018	0.043

Table 5.12: Standard Mean Differences of propensity score covariates between treatment group $1_{H2,WD>0}$ and control group $0_{H1,H2;WD>0}$ by datasets.

	Complete cases	Imputed datasets, min	Imputed datasets, mean	Imputed datasets, max
Age	0.045	0.004	0.006	0.006
Sex	0.295	0.023	0.027	0.038
Occupation	0.021	0.010	0.016	0.020
Industry	0.685	0.045	0.049	0.055
Q.Year	0.185	0.008	0.013	0.023
DiabetesK	0.015	0.001	0.010	0.024
WD	0.161	0.023	0.027	0.037
Insufficient.Job.Control	0.099	0.001	0.004	0.007
Work.Life.Conflict	0.034	0.004	0.006	0.009
Strain.Due.to.Rewarding	0.027	0.003	0.008	0.015
Lack.of.Social.Support	0.021	0.006	0.010	0.015
Dissatisfied	0.092	0.006	0.006	0.006
Any.Work.Problem	0.012	0.002	0.008	0.011
Alcohol.Consumption	0.205	0.004	0.048	0.128
BMI	0.073	0.004	0.015	0.023
Depressive.Symptoms	0.068	0.007	0.009	0.012
Pain.and.Physical.Impairment	0.047	0.010	0.016	0.037
Physical.Activity	0.083	0.011	0.013	0.016
Physical.Limitation.Work	0.195	0.030	0.060	0.104
Problems.with.Hearing	0.120	0.006	0.012	0.019
Problems.with.Vision	0.095	0.003	0.011	0.016
Self.Reported.General.Diseases	0.105	0.011	0.013	0.015
Self.Reported.Symptoms	0.034	0.017	0.025	0.041
Sleep.and.Alertness	0.068	0.012	0.014	0.019
Sick.Leave.Days.Before	0.003	0.003	0.007	0.013
Healthcare.costs.before	0.077	0.002	0.007	0.016

Table 5.13: Standard Mean Differences of propensity score covariates between treatment group $1_{H1,WD=0}$ and control group $0_{H1,H2;WD=0}$ by datasets.

	Complete cases	Imputed datasets, min	Imputed datasets, mean	Imputed datasets, max
Age	0.234	0.009	0.047	0.091
Sex	0.040	0.004	0.037	0.073
Occupation	0.209	0.023	0.036	0.052
Industry	0.630	0.042	0.112	0.161
Q.Year	0.052	0.002	0.020	0.081
DiabetesK	0.114	0.003	0.010	0.025
WD	0.000	0.000	0.000	0.000
Insufficient.Job.Control	0.017	0.001	0.008	0.014
Work.Life.Conflict	0.022	0.001	0.006	0.014
Strain.Due.to.Rewarding	0.007	0.004	0.008	0.017
Lack.of.Social.Support	0.002	0.001	0.013	0.019
Dissatisfied	0.023	0.001	0.010	0.018
Any.Work.Problem	0.011	0.002	0.010	0.018
Alcohol.Consumption	0.030	0.008	0.149	0.284
BMI	0.313	0.029	0.058	0.090
Depressive.Symptoms	0.117	0.005	0.015	0.027
Pain.and.Physical.Impairment	0.153	0.009	0.023	0.047
Physical.Activity	0.114	0.003	0.029	0.081
Physical.Limitation.Work	0.093	0.041	0.095	0.185
Problems.with.Hearing	0.235	0.036	0.133	0.231
Problems.with.Vision	0.306	0.015	0.065	0.118
Self.Reported.General.Diseases	0.103	0.019	0.040	0.057
Self.Reported.Symptoms	0.114	0.009	0.038	0.057
Sleep.and.Alertness	0.090	0.008	0.039	0.086
Sick.Leave.Days.Before	0.048	0.007	0.023	0.062
Healthcare.costs.before	0.014	0.004	0.007	0.014

5.6 The framework and models

The Average Treatment Effect of the net benefits of targeted occupational health interventions was formulated as the framework to answer the main research question. As described in the section 4.4 the ATE with IPW was given by

$$ATE = 1/n \sum (Z_i Y_i / e_i) - 1/n \sum ((1 - Z_i) Y_i / (1 - e_i)), \tag{5.7}$$

where n was the number of subjects, the propensity score e_i of each subject i was the probability of treatment assignment conditional on the baseline characteristics described in the subsection 5.4.3, and Z_i was the treatment received ($Z = 1$ for active treatment and $Z = 0$ for control treatment). Altogether, five different outcomes Y were analyzed. The main outcome of interest was the net benefits of targeted occupational health interventions: $Y_i = \text{Net Benefits}_i$. In addition, the relevant components of the net benefits were analyzed separately as outcomes to see how the treatment affected on the formulation of the net benefits. The net benefits per each employee i were given by

$$\text{Net Benefits}_{\text{i}} = \text{Benefits}_{\text{i}} - \text{Investment Costs}_{\text{i}}, \tag{5.8}$$

where

$$\begin{aligned} \text{Benefits}_{\text{i}} = & -\text{Costs of Short-Term Disability}_{\text{i}} + \\ & (-\text{Costs of Long-Term Disability}_{\text{i}}) \end{aligned} \tag{5.9}$$

and

$$\begin{aligned} \text{Investment Costs}_{\text{i}} = & \text{ Health Survey Costs}_{\text{i}} + \\ & \text{Health Care Utilization Costs}_{\text{i}}. \end{aligned} \tag{5.10}$$

Thus, the benefits in the net benefit framework were defined as the negations of the costs of short-term and long-term disability per employee. When the disability benefit costs or sickness absence costs decrease, the benefits increase. The disability benefit costs and sickness absence costs included estimations of both the direct costs and indirect costs that result to the society from the work input losses. Therefore

$$\begin{aligned} \text{Costs of Long-Term Disability}_{\text{i}} = & \text{ Direct Disability Benefit Costs}_{\text{i}} + \\ & \text{Indirect Disability Benefit Costs}_{\text{i}} \end{aligned} \tag{5.11}$$

and

$$\begin{aligned}\text{Costs of Short-Term Disability}_{\text{i}} = {} & \text{Direct Sickness Absence Costs}_{\text{i}} + \\ & \text{Indirect Sickness Absence Costs}_{\text{i}}.\end{aligned} \tag{5.12}$$

The costs of short-term and long-term disability were estimated as described in the section 5.4.2. The costs of short-term disability were the sum of the direct and indirect sickness absence costs, and the costs of long-term disability were the sum of the direct and indirect disability benefit costs. The indirect sickness absence costs were estimated twice as high as the direct sickness absence costs, as estimated by The Confederation of Finnish Industries EK (Kaukinen & Saukkonen 2009). The indirect disability benefit costs were estimated as high as the direct disability benefit costs. A sensitivity analysis was conducted with only direct costs to see how the indirect and direct costs affect on the net benefits of the treatment.

Eventually treatment effects on five outcomes of interest were analyzed: the net benefits, the benefits, costs of long-term disability, costs of short-term disability, and the investment costs. The ATEs were analyzed with Analysis of Covariance with relevant covariates and the IPWs. The covariates chosen for the ANCOVA models were the number of disability risk factors, the number of sick leave days within 12 months before the health survey, and the employee's age. These covariates showed the highest correlation with the net benefits. All five models built to test ATE on the five outcomes included the same covariates so that the results would remain comparable and able to be viewed as the breakdown of the net benefits.

Chapter 6

Results

The results to the main research question are presented in this chapter. The section 6.1 presents the breakdown of the net benefits of targeted occupational health interventions by comparing treated employees with a disability risk to untreated employees with a disability risk. The section 6.2 demonstrates the robustness of the results with three sensitivity analyses.

6.1 The net benefits of targeted occupational HIs

The net benefits of targeted occupational health interventions were positive in the research setting (The table 6.1). The Average Treatment Effect on the net benefits was 1,875 euros with a 95% confidence interval from -759 to 4,509 euros (p-value: .155) when employees who had been identified with a disability risk (WD>0) and had attended to a targeted occupational survey-driven health check within 6 months after the survey were compared to high-risk employees who had not attended to any health check within 12 months after the survey. The results were pooled from the data analyses on the five imputed datasets generated with MICE. The comparison groups were balanced with IPWs that had been formed from the propensity scores estimated to each employee. The results were formed with an ANCOVA model with three covariates: the employee's number of work disability risk factors, the number of sickness absence days within 12 months before the health survey, and the employee's age.

The net benefits resulted almost entirely from the increase of the benefits gained from long-term disability prevention. The ATE on the benefits was 1,867 euros with a 95% confidence interval from -767 to 4,500 euros (p-value: .156). The ATE on the disability benefit costs was -1,963 euros with a 95% confidence interval from -4,362 to 437 euros (p-value: .102). The ATE on the sickness absence costs was instead positive but less than an average sickness absence day cost per employee: 96 euros with a 95% confidence interval from -721 to 913 euros (p-value: .814). The ATE on the investment costs was -8 euros with a 95% confidence interval from -24 to 8 euros (p-value: .297).

Table 6.1: The results. The breakdown of the net benefits of targeted occupational health interventions.

Outcome	ATE, euro	95% CI, euro	p-value
Net Benefits	1,875	-759 — 4,509	.155
Benefits	1,867	-767 — 4,500	.156
Disability Benefit Costs	-1,963	-4,362 — 437	.102
Sickness Absence Costs	96	-721 — 913	.814
Investment Costs	-8	-24 — 8	.297

Average Treatment Effect (ATE) describes the average difference between treated and untreated employees. The treatment group ($1_{H1,WD>0}$) included employees with a disability risk (WD>0) who received treatment, i.e. attended to a targeted occupational survey-based health check within 6 months after the health survey. The comparison group ($0_{H1,H2;WD>0}$) included employees with a disability risk who did not attend any health check within 12 months after the health survey. The results were pooled from the data analyses conducted on the five imputed datasets generated with MICE. The groups were compared to each other with IPWs formed with the propensity scores estimated to each employee.

6.2 Sensitivity and robustness

The robustness of the results was tested with three sensitivity analyses. First, only the direct net benefits of targeted occupational health interventions were analyzed by considering only the direct benefits resulted from the disability prevention. Second, the impact of the speed of access to treatment was analyzed by comparing the employees (with a disability risk) who did not attend the targeted occupational health intervention within 6 months but in between 6 and 12 months after the survey to those employees (with a disability risk) who did not attend to any occupational health intervention within 12 months after the survey. The final sensitivity analysis was conducted on employees who had not been identified with a disability risk.

6.2.1 The direct net benefits of targeted occupational HIs

The table 6.2 shows the results from a sensitivity analysis where only the direct benefits and cost were analyzed. Other parameters were similar to the main analysis. The ATE on the net benefits was 958 euros with a 95% confidence interval from -307 to 2,222 euros (p-value: .130). The net benefits were again almost entirely formed of the increase of the benefits resulted from long-term disability prevention. The ATE on the benefits was 949 euros with

Table 6.2: Sensitivity analysis I. The breakdown of the direct net benefits of targeted occupational health interventions.

Outcome	ATE, euro	95% CI, euro	p-value
Net Benefits	958	-307 — 2,222	.130
Benefits	949	-315 — 2,214	.133
Disability Benefit Costs	-981	-2181 — 218	.102
Sickness Absence Costs	32	-240 — 304	.814
Investment Costs	-8	-24 — 8	.297

Average Treatment Effect (ATE) describes the average difference between treated and untreated employees. The results account only for the direct costs and benefits. The treatment group ($1_{H1,WD>0}$) included employees with a disability risk (WD>0) who received treatment, i.e. attended to a targeted occupational survey-based health check within 6 months after the health survey. The comparison group ($0_{H1,H2;WD>0}$) included employees with a disability risk who did not attend any health check within 12 months after the health survey. The results were pooled from the data analyses conducted on the five imputed datasets generated with MICE. The groups were compared to each other with IPWs formed with the propensity scores estimated to each employee.

a 95% confidence interval from -315 to 2,214 euros (p-value: .133). The ATE on the disability benefit costs was -981 euros with a 95% confidence interval from -2,181 to 218 euros (p-value: .102). The ATE on the sickness absence costs was 32 euros with a 95% confidence interval from -240 to 304 euros (p-value: .814). The ATE on the investment costs was equal to the results of the main analysis.

6.2.2 The net benefits of targeted occupational HIs with slower treatment access

The table 6.3 shows the results from a sensitivity analysis where the treated employees received access to treatment between 6 and 12 months after the health survey (instead of receiving treatment within 6 months after the survey). Other parameters were similar to the main analysis. The ATE on the net benefits was 2,368 euros with a 95% confidence interval from -695 to 5,433 euros (p-value: .122). The net benefits were again almost entirely dominated by the increase of the benefits resulted from long-term disability prevention. The ATE on the benefits was 2,360 with a 95% confidence interval from -705 to 5,425 euros (p-value: .124). The ATE on the disability benefit costs was -2,062euros with a 95% confidence interval from -4,723 to 600 euros (p-value: .122). The ATE on the sickness absence costs was -298 euros with a 95% confidence interval from with a 95% confidence interval from -1,376 to 779 euros (p-value: .580). The ATE on the investment costs was -8 euros with a 95% confidence interval from -29 to 12 euros (p-value: .420).

Table 6.3: Sensitivity analysis II. The breakdown of the net benefits of targeted occupational health interventions with slower access to treatment.

Outcome	**ATE, euro**	**95% CI, euro**	**p-value**
Net Benefits	2,368	-696 — 5,433	.122
Benefits	2,360	-705 — 5,425	.124
Disability Benefit Costs	-2,062	-4,723 — 600	.122
Sickness Absence Costs	-298	-1,376 — 779	.580
Investment Costs	-8	-29 — 12	.420

Average Treatment Effect (ATE) describes the average difference between treated and untreated employees. The treatment group ($1_{H2,WD>0}$) included employees with a disability risk (WD>0) who received treatment, i.e. attended to a targeted occupational survey-based health check between 6 to 12 months after the health survey. The comparison group ($0_{H1,H2;WD>0}$) included employees with a disability risk who did not attend any health check within 12 months after the health survey. The results were pooled from the data analyses conducted on the five imputed datasets generated with MICE. The groups were compared to each other with IPWs formed with the propensity scores estimated to each employee.

6.2.3 The net benefits of occupational HIs targeted at employees without a disability risk

The table 6.4 shows the results from a sensitivity analysis where treatment was targeted at employees without a disability risk identified (WD=0). Other parameters were similar to the main analysis. The ATE on the net benefits was 225 euros with a 95% confidence interval from -3,507 to 3,957 euros (p-value: .904). The ATE on the benefits was 227 with a 95% confidence interval from -3,506 to 3,959 euros (p-value: .904). The ATE on the disability benefit costs was -781 euros with a 95% confidence interval from -4,615 to 3,054 euros (p-value: .684). The ATE on the sickness absence costs was 554 euros with a 95% confidence interval from 256 to 852 euros (p-value: $<$.001). The ATE on the investment costs was 2 euros with a 95% confidence interval from -6 to 10 euros (p-value: .676).

Table 6.4: Sensitivity analysis III. The breakdown of the net benefits of occupational health interventions targeted to employees without a disability risk.

Outcome	ATE, euro	95% CI, euro	p-value	
Net Benefits	225	-3,507 — 3,957	.904	
Benefits	227	-3,506 — 3,959	.904	
Disability Benefit Costs	-781	-4,615 — 3,054	.684	
Sickness Absence Costs	554	256 — 852	<.001	(***)
Investment Costs	2	-6 — 10	0.676	

Average Treatment Effect (ATE) describes the average difference between treated and untreated employees. The treatment group ($1_{H1,WD=0}$) included employees without an identified disability risk (WD=0) who received treatment, i.e. attended to a targeted occupational survey-based health check within 6 months after the health survey. The comparison group ($0_{H1,H2;WD=0}$) included employees without an identified disability risk who did not attend any health check within 12 months after the health survey. The results were pooled from the data analyses conducted on the five imputed datasets generated with MICE. The groups were compared to each other with IPWs formed with the propensity scores estimated to each employee.

Chapter 7

Discussion & Conclusions

The results of the present study show that targeted occupational health interventions are likely to impose positive net benefits to the society. The Average Treatment Effect on the net benefits per each employee that had been identified with a disability risk, 1,875 euros with a 95% confidence interval from -759 to 4,509 euros (p-value: .155), can be considered worthwhile to the society. The net benefits were the most dominantly gained from the prevention of long-term disability. The treatment was not effective on short-term disability or total health care utilization costs per employee.

The results show that occupational health interventions are able to prevent long-term disability when they are targeted to employees with a high risk for disability. The results were similar in all sensitivity analyses that were conducted on high-risk employees. This finding supports the hypothesis that targeted occupational health interventions are effective and net beneficial in disability prevention. These results complement the previous literature since cost-effectiveness of targeted occupational health interventions has previously been studied mostly from the perspective of short-term disability.

The results were partly against the previous research of e.g. Taimela et al. (2008) (2007) since the treatment was not effective on the costs of short-term disability in the present study. When targeting occupational health interventions for high-risk employees within 6 months after the survey, all positive benefits were gained from the decrease of disability benefit costs. The ATE on the sickness absence costs was smaller than one sickness absence day cost per employee and far from statistical significance. Reason for this may be that the number of work disability risk factors was chosen as the most relevant predictor for disability and that the previous studies may have not underlined the importance of health problems. One reason for this may have also been in the research setting. The previous studies have focused on the prevention of sickness absence. Therefore, the occupational health care professionals that have conducted the health checks in the previous research settings may have focused more on the causes of short-term disability rather than disability as a whole. The present study was observational and without predetermined restrictions to sickness absences the occupational health care professionals may have focused more on long-term disability rather than sickness absence when discussing solutions for disability prevention.

The ATE on the investment costs (-8 euros, p-value: .297) indicate that the health care utilization costs of the treatment group and the control group did not differ from each other. The results regarding the investment costs were similar in all sensitivity analyses. We can conclude that targeting occupational health interventions do not increase employees' health care utilization costs even though the treated employees attended the health check and many were be directed to additional health care services. A possible explanation for this is that offering preventive care decreases the need for care in the future. This explanation is consistent with the results of for example Taimela et al. (2008).

Based on the results, 51% of the net benefits of the targeted occupational health interventions are formed of direct costs and 49% of indirect costs. Because the net benefits were almost entirely formed of the savings resulted from prevention of long-term disability, the results are highly sensitive to the estimations on indirect costs of long-term disability. The indirect costs of short-term disability have previously been estimated twice as high as the direct short-term short-term disability costs. When estimating indirect costs of long-term disability, the frictional costs resulting from reorganization, productivity losses and recruitment, for example, can be considered as one-off costs that result when the short-term disability turns into long-term disability but the societal losses of tax income remain as long as the employee stays outside the labor force. Very few estimations have been conducted on the indirect costs of long-term disability in Finland but the estimations of the present study can be considered realistic or even conservative.

One might expect that offering faster treatment access would result as higher net benefits. However, the results of the research setting could not verify this hypothesis. A likely explanation for this is that the employees were invited to the targeted health checks in a prioritized order. If this holds, it can be concluded that the prioritization of the employees was successful: the employees who were invited to the health check between 6 and 12 months after the survey were already healthier than those who were invited to the survey first. The limitation of the analysis was that the timing of the invitations for untreated employees was not known. 86 percent of the treated attended the targeted health check within 6 months after the survey. It is reasonable to assume that most of the high-risk employees who did not attend the health check were invited to the health check within 6 months after the survey as well. The untreated group can therefore be considered to contain more ill employees than the treatment group of the sensitivity analysis II. The results considering the employees with slower treatment access can therefore also be considered reasonable. On the other hand, if the previous reasoning holds, it can be concluded that the results of the main analysis would be even higher if it would have been possible to distinguish those untreated high-risk employees who had been invited to the health check between 6 to 12 months after the survey.

The results underline the relevance of targeting the interventions for employees that face a high risk for disability. When targeting occupational health interventions for those employees who had not been identified with a disability risk, the 90% confidence interval from -3,506 to 3,959 euros (p-value: .904) indicates that the treatment was not effective on the benefits of long-term disability prevention. The results also indicate that some unrevealed predictors for long-term disability might still exist that the survey or its analysis do not identify. This is cnsistent with the previous research that not all disability can be predicted.

When comparing the employees in the treatment and control groups without work disability risk factors, the ATE on the costs of short-term disability was higher for those employees who attended the health check (95% CI from 256 to 852 euros, p-value: <.001) but the causal relation of this finding can be considered questionable. One possible explanation for this can be that the treated low-risk employees were and felt more ill after the survey and had therefore a higher incentive to attend the health check.

The features of the research setting and the quality of the data set some limitations to the present study. Some of the limitations were managed with statistical methods in a reasonable way. The missingness was solved with multivariate imputation. The missing salary and disability benefit cost data was predicted from the data on average salaries. Some limitations still exist because the exact timings of the health check and the invitation to the health check were missing. As described above, this limitation is however more likely to restrain the results than overemphasize them. The volatility of the costs of disability were so high that it was very hard to reach statistical significance with the models but the relevance of the results can also be evaluated from the 95% confidence intervals of the ATEs.

Some additional limitations to the accuracy of the results occurred because the follow-up took place in an open system. Costs of other possible actions conducted at worksites on top of the occupational health services or at the employees' private lives were not known and therefore could not have been considered in the analysis. Moreover, not all disability can even be predicted since short-term and long-term disability can always occur due to accidents and other events of stochastic nature. Eliminating accidental causes of disability from the analysis would be reasonable when the objective is to examine how targeted occupational health interventions prevent disability that has even any opportunity to be predicted and prevented. For future research, diagnoses of the causes of disability and an objective evaluation of the existed prediction opportunities of the causes would most likely increase the richness of the results and their conclusions.

The accuracy of the results was primarily limited by the observational research setting. The impact of obvious selection bias was dealt with propensity scores and IPW as far as possible. However, results from an observational study can never be considered as reliable as results gained from a randomized research setting. The statistical methods used enable to reach as unbiased estimates as possible. A Randomized Controlled Trial would be an ideal research setting but it would be very hard to reach 20,000 subjects to construct a RCT.

To summarize, the results of the present study supplements the previous research by numerous perspectives. Targeted occupational health interventions have previously been proven as cost-effective on short-term disability in a randomized research setting. The present study revealed the net beneficial effectiveness of targeted occupational health interventions on long-term disability in an observational research setting. No study has earlier been conducted with as holistic view on both short-term and long-term disability prevention. The prevention of long-term disability has not previously been analyzed with as high a sample size and as wide sensitivity analyses. No study before has previously formulated the net benefits of targeted occupational health interventions.

The results also complement some previous findings but also question some others. The results support the previous research that state that multiple work disability risk factors are indeed relevant predictors for disability. However, the results also indicate that there might also be other relevant predictors for disability that were unable to be identified with the survey. The results also indicate that the care that prevents long-term disability may not be more effective on short-term disability than usual care. All in all, the results clearly supported the initial hypothesis that the process behind targeted occupational health interventions is able to distinguish a subgroup of individuals who face a high risk for disability, and that targeting occupational health interventions for this group of individuals is most likely net beneficial for the society.

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