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A THREE-YEAR EVALUATION OF A MUNICIPAL DISEASE MANAGEMENT PROGRAM FOCUSED ON HEALTH RISK REDUCTION AND IMPROVEMENTS IN ABSENTEEISM RATES

BY

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Degree to be awarded: M.P.H.
Career MPH

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An abstract of
A Thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
In partial fulfillment of the requirements of the degree of
Master of Public Health in the Career MPH program
2013

Abstract

A THREE-YEAR EVALUATION OF A MUNICIPAL DISEASE MANAGEMENT PROGRAM FOCUSED ON HEALTH RISK REDUCTION AND IMPROVEMENTS IN ABSENTEEISM RATES

By

Warren Brooks Sayre

Objective: To evaluate the disease management program implemented by the City of Knoxville in terms of its effects on employee biometric and absence outcomes.

Methodology: Administrative and biometric data were collected from 2008-2011 on City of Knoxville employees. Those eligible for disease management self-selected participation, and the two groups were compared statistically in terms of year-to-year changes in biometric measures and in absence hours.

Results: Descriptive analysis revealed statistical differences in the participant and nonparticipant groups at baseline. A difference-in-difference analysis of changes in biometric and absence data showed no statistically significant differences between participants and nonparticipants with the exception of diastolic blood pressure, although that outcome was clinically trivial. The analysis of administrative data showed no statistical reduction in absence when comparing the participant and nonparticipant groups ($p = 0.58$).

Conclusion: Selection bias, inaccurate data collection, and confounding factors prohibit broader attribution of evaluation findings to the general population. Improved evaluation design, including improved case-control matching to minimize confounding and bias and improved data collection to assure accuracy, would better serve future evaluations of the myHealth Program. Inherent variation in data related to absence, make administrative data analysis less useful. Adding productivity questions to an employee health risk assessment may be a better method to measure absence variation as a primary outcome.

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Acknowledgements

Thank you to the faculty and staff at the Rollins School of Public Health, Career Masters in Public Health (CMPH) Department. The knowledge you have imparted and the support you have given in this learning process have been tremendous. You made an unconventional educational experience easy and, dare I say, fun.

Thank you to my Committee Chair, Ron Goetzel. Ron, I have appreciated your work for years as a thought leader in the area of health and productivity. The opportunity to interact with you through this thesis process is not one that I could have even dreamed of.

Thank you to my Field Advisor, Kathy Brown. Knox County is so fortunate to have you as part of the public health team. You opened doors for me. You opened my eyes to population health. Your edits and advice on my thesis were invaluable. More than all this, your friendship is an unexpected jewel discovered through the CMPH process.

To my children: Elijah, Benjamin, and Lydia. You all are so precious to me, and I thank you for the grace to be a part-time Dad during the MPH process. You inspire me to aspire to try to do great things, as an example to you all, but also to leave a legacy.

To my incredible, fantastic wife, Angie: Thank you for enduring the whole process with grace and beauty. I could never have achieved this milestone without your support and patience (and word-smithing).

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Chapter 1: Introduction to Study

Introduction

The purpose of this study is to evaluate the effectiveness of disease management interventions in the City of Knoxville's myHealth Program in terms of primary and secondary outcome measures of biometric changes and absence improvement. Disease management (DM), as defined by the Care Continuum Alliance, is a "system of coordinated healthcare interventions and communications for populations with conditions in which patient self-care efforts are significant."[1] Since the early 1990s, employers and commercial health plans deployed various DM programs many of which focus on type-2 diabetes, cardiovascular disease, high blood pressure, high serum cholesterol, chronic lung disease, and obesity to improve the quality of healthcare while controlling cost. Diabetes Type 2, cardiovascular disease, high blood pressure, high cholesterol, chronic lung disease, and obesity are often preventable diseases associated with latent phases where biometric risk factors are measureable in laboratory testing, but are not affecting the individual in a symptomatic way. These conditions contribute significantly to lost productivity in the workplace from employee "presenteeism" (coming to work but having health issues affect the ability to perform at an optimal level) and absenteeism. A national survey performed in 2012 found that almost two thirds of employers who offer health benefits also support at least one component of a workforce health promotion program.[2] These types of programs are an attempt to combat the high cost of presenteeism and absenteeism through employee engagement in evidence-based interventions.

A growing volume of research in wellness, prevention, and disease management points toward the financial benefit of such programs, both in direct health costs and health-related work productivity measures.[3] Bolnick, *et al*. estimate a potential savings of 18.4% in annual medical costs per working age adults linked to improvement in health through health and chronic disease management.[4] By improving employee health, studies have shown reductions in health care costs, absenteeism, and disability claims as well as improved worker productivity. [5-10] Henke *et al*. 2011, estimated a $1.88 - $3.92 return on investment at Johnson & Johnson associated with having in place a long-term health promotion program targeting high risks in employee obesity, hypertension (HTN), hypercholesterolemia, tobacco use, physical inactivity, and poor nutrition. [9] A systematic review performed by The Community Guide to Preventive Services, housed at the Centers for Disease Control and Prevention (CDC) and led by Dr. Robin Soler, evaluated the effectiveness of programs using health risk assessments as well as other components of health promotion in the past thirty years.[11] Fifty-one studies met the stringent inclusion criteria established by the Task Force. The general conclusion was that theory-based, well-designed programs, accompanied with assessments of health risks with feedback to the employee, did improve behavioral, biometric, and financial outcomes including absenteeism. Debra Lerner, PhD, and colleagues performed a systemic review of studies of employee-focused health promotion and wellness programs performed since January of 2000. [12] The purpose of the Lerner's *et al.* review was to assess whether such programs actually demonstrated economic impact. In general, they found the evidence was "limited and inconsistent." The majority of the studies used self-reported absence data, which has been demonstrated to be comparable to administrative data in a 2009 study by Short *et al.,* particularly in short term recall (one month) compared to long term (annually)[6] Employer sponsored disease management programs tend to focus on high cost/high opportunity conditions such as diabetes, chronic lung disease, coronary artery disease, congestive heart failure, back pain, and depression.[11]

Setting

During the study period, The City of Knoxville, Tennessee (COK) employed approximately 1500 employees (full-time and part-time). In 2007 after a four-month ramp-up, the City began a comprehensive corporate wellness program called "myHealth" in conjunction with its occupational health clinic. In 2009, the myHealth Program enhanced the health coaching and disease management aspects of the program. The development and deployment of the myHealth Program was a collaborative effort between the City of Knoxville (COK) and Summit Medical Group (SMG), a large primary-care physician group in East Tennessee. In addition to services rendered at the City of Knoxville Health, Wellness, and Education Center (The Center), such as annual and pre-placement physicals, work injury visits and acute care visits, SMG engaged City employees in various venues for group and individual health coaching and disease management services.

Theoretical Framework

While many of the interventions were condition-specific, the myHealth Program also focused on whole-person self-care needs and risk reduction. Based on the chronic care model described by the MacColl Institute[13], SMG implemented programs that address self-management support, delivery system design, decision support, and clinical information systems to help channel productive interactions between the support team and an empowered patient.

Self-management support encompassed placing the proper knowledge, tools, and resources in the hands of individuals to allow them to manage their disease. The disease management services were provided by registered nurses, a certified diabetic educator, and/or an advanced-practice nurse. The training resources and curriculum were evidenced-based and were a modified version of the Institute for Clinical Systems Improvement's Health Care Guidelines[14] as well as other evidenced-based guidelines. SMG designed a delivery system to reduce issues of poor access and inconvenience to the employee. Connecting to the primary care provider through correspondence and phone calls, the disease management coach stressed the importance of enhancing the relationship between the patient and the treating physician. Wagner *et al.*, describe decision support and clinical information systems as pivotal elements to disease management.[15] In year one of the program, SMG implemented a personal electronic health record and combined several databases that were being utilized to collect biometric and health screening data. Once collected, these data were exported to the Healthcare 21 Data Cooperative to combine with administrative data. SMG and COK collaboratively analyzed data and stratified the population into risk tiers. Based on the risk tier assigned, disease management coaches would engage participants in developing a self-management plan for the year.

Research questions

The three main questions of this research are:

1. Compared to nonparticipants, did participants in the disease management program achieve significant improvements in biometric measurements of body mass index (BMI), total cholesterol, systolic blood pressure, diastolic blood pressure, low density lipoproteins (LDL), and/or blood glucose?

   Null hypothesis – disease management participation will not improve biometric measures mentioned above.

2. Compared to nonparticipants, did participants in the disease management program achieve significant improvements in absenteeism?

   Null hypothesis – disease management participation will not improve absenteeism.

3. Was a dose-response effect observed with the number of disease management visits affecting absence?

   Null hypothesis – there is no relationship between the number of coaching visits and absenteeism.

Purpose and Rationale

Worksite disease management and wellness/prevention programs have shown significant improvements in direct and indirect health costs. Most studies demonstrating absenteeism reduction are based on self-reporting through productivity questionnaires. This study is based on administrative and biometric data and attempts to correlate absence reduction with biometric improvements.

Chapter 2: Review of the Literature

Introduction to the Review of Literature

The literature review is focused on the questions: “Why is disease management important from a cost perspective?”: “What are the key elements of disease management?” and “How have various disease management and wellness endeavors affected biometric and absenteeism outcomes?” The review is segmented into correlation (cross-sectional) and large interventional studies in the public and in the private sector focused on biometric and productivity outcomes.

Body of Review of Literature

In order to ascertain who generally engages in disease management, Melinda Buntin, PhD *et al.*, performed an observational study on data from a large health plan.[16] In general, patients who enroll in disease management tend to differ significantly from those who do not in regards to demographics, cost, utilization, and quality metrics. For example, more females enrolled, and there were more individuals over 50. For cost, enrollees had higher cost and utilization of office visits and ER visits.

Many correlation studies have been published to help public and private disease management programs focus interventions on high-cost, high-opportunity disease conditions. The conditions tend also to be the focus of the health literature at large, supporting evidence-based interventions – a hallmark of disease management. Ron Goetzel, PhD and colleagues, in an article published in the *Journal of Occupational and Environmental Medicine* in 2003, deduced that, on average, employers paid $703/employee/year for each individual having at least one of the top 20 chronic diseases.[17] Utilizing the Work Productivity and Activity Impairment Questionnaire, Lenneman *et al*., 2011, demonstrated a dose-response relationship between health risk status and productivity impairment. [18] Henke, Carls *et al*., 2010, surmised that a 1% annual decrease in health risks assessed would yield an annual savings of $83-103 per capita (this included medical, worker's compensation, and short-term disability savings). [19] Disease-specific absence hours from a self-reported study demonstrated the average additional hours for asthma (12 hrs), diabetes (2 hrs), CAD (6.8 hrs), HTN (0.9 hrs) compared to nondiseased individuals.[20] Kowlessar *et al*., 2011, looked at biometric markers and their correlation with absenteeism and found that patients with elevated blood glucose had an associated increase in absence costs of $146 per employee per year while elevated weight demonstrated an associated increase of $113 per employee per year.[21] Additional studies were found that related to specific conditions and anticipated outcomes. Patients with asthma demonstrated an average of $191 in increased incremental costs of absenteeism compared to controls. [22] A study from 2002 estimated the average work loss attributed to diabetes was 1.7 to 2.2 times that of nondiabetics [23]. Many studies identified a correlation and even curvilinear type association between weight and absence.[24-26] Pertinent to the current study, Poston *et al*, 2012 demonstrated greater risk for injury-related absenteeism in a population of fire fighters who were obese compared to those with normal weight.[27]

In this section of the literature review, elements of public and private DM are briefly described with discussion of pertinent findings. From 1999 until the present, Medicare has been funding and monitoring many disease management demonstration projects (DMDP). The key elements of DMDPs are telemedicine, telemonitoring, case management, and care coordination.[28] Of note, care coordination and disease management are often used interchangeably. Most of the DMDPs employed registered nurses (RNs) to provide telephonic health education/coaching, patient self-management training related to medication adherence, and methods for managing disease exacerbation.[29] Some of the DMDPs integrated care with physicians, but most did not. Results did not show Medicare expenditure reductions, nor did they show significant improvements in process measures such as achieving certain secondary prevention measures for patients with the proscribed disease.[29] Since the research on the DMDPs did not obtain biometric data, no corollary information related to intermediary outcomes is available for comparison.

DM interventions assessed in the private sector show more promising results. In a study conducted by Ginger S Carls, PhD, and colleagues, data from the Thomson Reuters Marketscan Commercial Claims and Encounters and Health and Productivity Management Research

Database revealed that for individuals with diabetes, hypertension, hyperlipidemia, and chronic lung disease, improved medication adherence, a focus of most disease management programs, reduced absences between 1.7 to 7.1 days. [30] A study analyzing internal administrative database of a Fortune 100 company showed a risk reduction for all participants (with and without disease) in its health and productivity management program of 3 ½ days in health-related absences/year (self-reported). [31] John Nyman and his colleagues at the University of Minnesota demonstrated a return on investment in Year 3 for the general disease management program they implemented at the university; however, the savings were related to reduction in healthcare costs rather than absenteeism.[32] An earlier multi-site study on worksite programs from the late 90s showed a 25-30% reduction in medical and absence costs for individuals who were in a wellness program for over three years. [33]

The remainder of the body of the literature review summarizes research on interventional programs that focused on specific diseases or conditions and productivity outcomes. The "Tune Up Your Heart" Program showed a modest improvement in the intervention group that improved cardiovascular disease risk factors, particularly blood pressure reduction, weight reduction, and tobacco cessation. [34] Research by Scott Ramsey, MD, PhD, and colleagues demonstrated that for individuals in their study population with diabetes, those engaged in disease management showed a reduction in medical costs and work loss compared to the control group (31-42% study population vs. 33-53% control group).[23] No interventional studies specifically targeting hyperlipidemia were discovered, although reduction in LDL cholesterol was a secondary outcome in many studies including Heiner Berthold, MD, PhD, and colleagues work in a diabetes focused DMP which showed that participants met LDL reduction targets.[35] Allen *et al*. showed a moderate increase in the direct costs of COPD over the study period, but a marked decrease in the indirect costs (absenteeism and presenteeism). [36] Another study of COPD patients showed nine hours' more "controllable absence" than the control group.[37] Since smoking is highly related to the development of COPD, it is important to note that former smokers in the study had 1.6 fewer absence days than current smokers. [37]

Clearly there are strong correlations between chronic disease, as well as health risk factors, and absenteeism. The majority of the studies cited in the literature are from self-reported absence data. Few studies were found that looked at secondary outcomes such as biometric markers and absenteeism. Many of the building blocks of disease management programs, namely patient empowerment, medication adherence, and secondary prevention screenings and services, were evaluated and reported in the literature review.

Chapter 3: Methodology

Introduction

Using data from 2008, 2009, 2010 and 2011, the Healthcare21 Data Cooperative collected information from employees' electronic health records and administrative claims data. This evaluation analyzed whether there was a statistical difference in claims, biometrics and absence data associated with employees with chronic conditions who participated in the myHealth Program compared to the nonparticipant group with similar chronic conditions.

Population and Sample

This study focused on employees covered by the City of Knoxville self-funded health plan who had chronic medical conditions as elucidated by claims data. The Healthcare 21 Data

Cooperative assigned disease status based on diagnosis-related groups (DRGs) using claims thresholds. The study sample was comprised of employees who had one or more chronic diseases (asthma, cardiovascular disease, high cholesterol, COPD, diabetes, HTN, and/or obesity) and who were enrolled in the City's comprehensive corporate wellness program called "myHealth." Knoxville had 1504 covered employees under its self-funded plan. Participation rates in the myHealth Program ranged between 52% and 64% over the study period. Of the 959 employees who were enrolled in myHealth, 583 had at least one chronic condition qualifying them for one-on-one health coaching/disease management services. Of these 583 employees, only 205 were consistently in the program for the three years of the study and had claims and biometric data for the 12 months prior to the study.

Program requirements included: completing an Annual Health Screening with biometrics, submitting a monthly affidavit of physical activity, attending quarterly education activity, or completing a health education activity. Participants also were required to attend a mandatory meeting with a health coach/care manager periodically if they were diagnosed with one of eight conditions (diabetes, HTN, high cholesterol, CAD, congestive heart failure [CHF], COPD, asthma, obesity) based on claims data or biometrics. Participants were identified by their member ID number which indicated whether they were enrolled in the myHealth program or were 'Medical Only" (enrolled in the health plan, but not participating in the DM program). Participants were offered a grace period if they failed to meet one of the above requirements for one quarter; however, if they failed to meet the requirements for a second quarter, they were dropped to Medical Only status.

Participant Group (PG)

There were additional requirements to be in the Participant Group study sample. Participant group subjects must also have had:

- One year (12 months) of claims and absence data prior to starting in the myHealth Program
- Participated in the myHealth Program for 36 months
- Claims and absence data for Year 3 of participation
- At least one of eight chronic conditions previously listed. If any members dropped out of the program at anytime during the 36-month study period, or if they did not have one of eight chronic conditions, they were excluded from the study.

Nonparticipant Group (NG)

To be categorized in the nonparticipant group, employees must not have participated in the myHealth Program at all during the 48 months of the study period. In addition, these employees must have had claims and absence data for Year 0 (12 months prior to the start date) as well as Year 3 of the study period. Employees in this group self-selected not to be in the program. Nonparticipants were excluded if they were involved in the myHealth Program at any time during the three-year study period or if they did not have at least one of eight chronic conditions mentioned previously. There were 115 employees in the Nonparticipant Group.

Comparison of Participants vs. Nonparticipants

The two cohorts were compared in the following categories by:

- Age (continuous)
- Employee subgroup: fire, police, other, public service (categorical)
- Age range (categorical)

- Conditions included asthma, CAD, CHF, cholesterol, COPD, DM, HTN, obesity (binomial categorical)
- Hourly income (continuous)
- Disease burden 1-8 (categorical)
- Annual income (continuous)
- Gender M/F (categorical)
- Annual pay range (categorical)

The two cohorts were also compared on the basis of biometric data that were collected by the Healthcare 21 Data Cooperative as provided by the wellness vendor. Absence data were collected by the City of Knoxville time-clock software. For the purposes of this study, only "sick leave" hours were considered, excluding hours delineated as annual leave, bereavement, comp time, "do not pay" (DNP), family sick leave, military leave, other leave, and worker's comp time.

The author performed a descriptive analysis on data from both participants and nonparticipants using the SAS 9.3 software PROC UNIVARIATE procedure for continuous variables of age, hourly pay rate, annual pay rate, first BMI, and last BMI. The "p" values for the student t-test were used to assess differences between the cohorts.

The SAS 9.3 System PROC FREQ procedure was used to assess categorical data for continuous variables of age range, annual pay range, BMI category, gender, disease burden, job category, and the presence of specific diseases (asthma, CAD, CHF, COPD, DM, high cholesterol, or

HTN--based on claims data). The 95% confidence intervals were calculated for all continuous variables utilizing OpenEpi software.

For Year 3 of the program, the author performed multivariate regression analysis using the SAS PROC LOGISTIC procedure to assess whether mean differences in absenteeism were affected by age, age range, gender, hourly pay rate, annual pay range, annual pay rate, job category, and the average number of coaching visits as well as the mean change in blood glucose, mean LDL change, mean BMI change, and disease burden.

Chapter 4: Results

The results of the study were obtained through a series of analyses. The tables of supporting data are presented in Appendix D of this Thesis.

Descriptive Analysis

As demonstrated in Table 1, The Participant Group was statistically different than the Nonparticipant Group on almost every demographic variable. The PG members were older, had a higher number of female participants, and a greater ratio of general government workers (p values < 0.01). Note, the number of police officers and fire fighters were the same in both the PG and NG. Although annual pay rate and annual pay range variables were not statistically different ($p = 0.14$ and $p = 0.38$ respectively), the PG did appear to have higher average incomes. Two outliers were dropped due to age greater than 70. One individual's annual pay measure was dropped because it was an outlier ($500). Eleven participants as well as nine nonparticipants had missing values for hourly and annual pay rate.

The participant and nonparticipant groups were compared on biometric values (Table 2). The groups were statistically dissimilar in weight classification (underweight, normal weight, class I obesity, class II obesity, morbid obesity) using chi square analysis ($p < 0.01$). The data indicate that a higher percentage of the participants fall into the obesity class II and the morbidly obese classification (implying poorer health). Additionally, body mass index measures for Year 0 were statistically similar ($p = 0.12$, Year 0). Biometric measurements demonstrate statistically similar mean total cholesterol ($p = 0.60$), mean LDL cholesterol ($p = 0.27$), and mean fasting glucose levels ($p = 0.24$) for Year 0 (2008) between the two groups, using paired t test, Satterthwaite equation (since the number of observations was unequal). Normal values of total cholesterol would be below 200 with an ideal value below 160 for the general population. An LDL cholesterol normal value would be below 130 with an ideal value of below 100. Mean systolic and diastolic blood pressures were statistically similar for both groups ($p = 0.40$ and 0.19 respectively).

Table 3 compares claims data between PG and NG. The groups were statistically similar in terms of disease burden (sum number of all eight chronic diseases) ($p = 0.06$) as well as each of seven individual diseases, although the lack of statistical difference is more likely due to small sample size rather than actual similarity. As examples, there is almost a 9% difference in the number of individuals with diabetes in the PG compared to NG, and PG individuals tend to have a higher number of comorbid conditions. COPD was the only disease in which the percentage of confirmed cases was higher in the NG than the PG; the PG had higher percentages in all other chronic diseases.

Table 4 shows the comparison of age, annual pay, and hourly pay among the four subgroups of workers in the City employee population (fire, general government, police, and public service).

There is a variation in age and pay between the subgroups, demonstrating that general government workers have higher average pay and are generally older.

Statistical Analysis

Biometric Outcome Analysis

Secondary outcomes of biometric changes (i.e., BMI, total cholesterol, LDL cholesterol, DBP, SBP, and glucose) were also analyzed. Year-to-year comparisons of total cholesterol, LDL, and fasting glucose within the PG and NG were analyzed with paired t testing (Table 5). The NG showed statistical improvement in total cholesterol comparing Year 2 with Year 0 ($p = 0.04$), but comparison of Years 1 and 3 to Year 0 showed no statistical variance. Years 1, 2, and 3 showed a statistically improved average LDL cholesterol compared to Year 0 in NG. No statistical difference was demonstrated in fasting glucose year to year in the NG. In the PG, all three years showed statistical improvement in total cholesterol and LDL cholesterol with trending greater differences year to year. No statistical improvement was noted in fasting glucose in any year in the participant group.

A difference in difference analysis was performed on glucose, LDL, cholesterol, BMI, systolic blood pressure, and diastolic blood pressure. The only statistically significant difference between the PG and NG was the change in diastolic blood pressure from Year 0 to Year 3 (3.6 mmHg difference, $p = 0.02$). All other comparisons between the PG and NG were similar in each year for each metric (Table 6).

Subgroups of fire, general government, police, and public service personnel were evaluated. Table 7 presents the results of this analysis, showing that the fire department NG experienced a statistical improvement in their total cholesterol in Year 1 while the general government PG improved in that year ($p = 0.01$). For all other subgroups, no statistical improvement was noted for Year 1. In Year 2, general government and police participants showed an average statistical improvement from Year 0. General government and police participants also showed statistical improvement in Year 3. The analysis demonstrated a similar pattern for LDL cholesterol and is displayed in Table 8. Although there were 50 people in the participant group who did not have all three years of their biometric data, both Table 7 and Table 8 indicate that the most significant changes in total cholesterol and LDL cholesterol were for employees in the general government subgroup.

The analysis of absence hours demonstrated no statistical differences between the PG and NG from year to year. (Table 6) Both groups had trending reduction in absence; however, both groups showed a trivial number of reduced absence hours. In Year 3, the NG group experienced a 1.30-hour reduction compared to Year 0. The PG likewise showed a modest 2.04-hour reduction. Comparing the two, the improvements were not found to be statistically different ($p = 0.58$). Table 9 further stratifies absence changes in each work group (fire, general government, police, and public service) showing a statistically significant reduction for the PG in absence in general government and police officers in Year 3 compared to Year 0 ($p = 0.01$ and 0.05). No other statistically significant changes were noted in the subgroup analysis for Years 1 and 2.

Chapter 5: Conclusions, Implications, and Recommendations

Introduction

The evaluation was set up in a retrospective design with a control group for comparison. Biometric and administrative data were measured over a three-year period with at least 12 months of claims and absence data in the year prior to the start of the intervention. There were significant differences in the nonparticipant group compared to the participant group at baseline (i.e., participants were generally older and had a higher percentage of females) although both groups were statistically similar in average annual pay rate and biometric measures (total cholesterol, LDL cholesterol, fasting glucose, and body mass index measurements) probably because the sample sizes were too small to detect statistically significant differences between groups.

Summary of study

The purpose of this evaluation was to determine whether participation in the City of Knoxville's disease management program led to improvements in biometric markers and reductions in absense hours among participants compared to nonparticipants. Additionally, the study assessed whether there was a dose-response relationship between the number of health coaching visits and improved employee attendance.

Based on a difference in difference analysis where participants in the myHealth Program were compared to those in the nonparticipant group, there were no statistically significant improvement in biometric markers (total cholesterol, LDL cholesterol, BMI, systolic blood pressure) in Year 3 of the program when compared to baseline, with the exception of diastolic blood pressure where a statsitically significant improvement was found (favoring participants) a in Year 3 when comparing participants and nonparticipants. Therefore, the null that disease management would produce no improvement in biometric readings is accepted as it pertains to total cholesterol and LDL cholesterol, systolic blood pressure and BMI. The null is rejected for diastolic blood pressure only. However, the anlysis did not control for baseline differences between participants and nonparticipants in terms of their demographic characteristics and health factors, so the conclusions drawn from this analysis should be interpreted with caution. Most notably, the presence or absence of significant findings may be a result of selection bias meaning that healthier or sicker individuals enrolled in the DM program or were more or less motivated to make health improvements prior to enrollment. The analysis also demonstrated no statistically significant differences between participants and nonparticipants in terms of the number of absence hours reported at the conclusion of the study compared to baseline. Therefore, the null hypothesis that participation in the Disease Management Program will not reduce absence hours is accepted.

Health coaching data were poorly collected and therefore no valid assessment was made as to whether the amount of health coaching (dose) did or did not improve absence hours (response).

Limitations and Delimitations

Limitations to this study fall into the categories of data capture and accuracy, sample size, selection bias, and confounding factors. Pertaining to data capture and accuracy, a limitation of this study is the sparse biometric data available on nonparticipants. Because nonparticipants were not required to complete the health screening or biometrics, comparisons on biometric changes between the participant and nonparticipant groups were limited. Some data were available from police and fire fighters as biometrics are a part of their annual fitness for duty examinations.

Participants should have received at least one coaching visit per year; however, 2009 was the first year that coaching and disease management were implemented. There were issues with capturing the number of coaching visits in Year 1 due to data entry errors. Inconsistent data capture and the utilization of several different databases for data capture in the early years of health coaching and disease management did not allow for dose-related effects to be adequately assessed. Several key staffing changes also occurred during the study period, which introduced variability in the quality and content of the coaching and disease management.

According to City of Knoxville officials, there are certain inaccuracies in the capture of absence data collection. Some departments are more apt to label sick leave as annual leave, which can skew the actual absence data. Another variation in sick leave data relates to fire fighters. Because they work 24-hour shifts, if they miss one shift, it is often counted as 24 hours of sick leave while in most other departments, each shift is eight hours.

Another limitation was the small sample size due, in part, to missing or incomplete data and a small population. Specifically, there were limited, eligible nonparticipant group members to adequately perform case-control matching. Limited sample size also precluded assessing specific disease conditions individually such as diabetes, CAD, or COPD. The smaller sample also prevented imputing values for missing or incomplete data.

Self-selection into the participant group introduced selection bias, and as other studies of this nature have indicated, the intrinsic motivation to improve one's health may be a stronger predictor of improved outcomes than the intervention itself. If the goal of the disease management program is to engage individuals with chronic conditions, then it would be expected the program would be designed in a way to encourage the participation of individuals with conditions amenable to health coaching and disease management.

In a multifaceted program like myHealth, it would be challenging to isolate specific interventions to see which are most effective. One facet that was not used in the comparison was the number of acute care visits at The Center. Participants in the myHealth Program have access to acute care which, one would postulate, could reduce absence by allowing participants to stay at work and be treated for acute illness. Another challenge to the study was the number of significant changes the employer made to the myHealth Program throughout the study period, causing a significant shift in the number of participants in the program. For example, the requirement for spouses and dependents to complete annual wellness assessments in order for the employee to be eligible for the program decreased the number of employees who stayed in the program. Conversely, allowing online educational programs rather than attendance at onsite lectures improved compliance with the quarterly educational requirements, which helped retain spouses and retirees in the program.

Changes in disease management staff in conjunction with the inability to manage the coaching visit data limited the ability to assess best practices among the various coaches. Improvements in decision support and "informatics" remedied this issue in the latter years of the study.

In order to address regression to the mean, both the PG and NG must have been eligible for disease management at the start of the study period. Normally, confounding would be addressed in a quasi-experimental model through case-control matching; however, our control sample size did not allow for adequate matching. Propensity scoring was considered, but also had limitations due to sample size and lack of biometric data in the control group.

Implications/Conclusions

While the PG and the NG are statistically different on many of the variables at baseline, making comparisons less relevant, the myHealth disease management program does appear to be engaging less healthy individuals in terms of their disease prevalence who may have more opportunities for improved outcomes and improved productivity. Modest reductions of absenteeism (-2.04 hours per person on average) were observed in the participant group comparing Year 3 to Year 0 of the study period. However, the nonparticipants also reduced their absence hours by 1.30 hours and there were no statistically significant differences between the two groups. There were many challenges to obtaining accurate data for employees' sick leave, and the only correlation with sick leave improvement in participants was the annual pay rate (p value = 0.02). Due to the myriad of limitations and confounding factors, the results of the retrospective analysis cannot be generalized to other populations, and the most appropriate conclusion to the analysis would be that the evidence is inconclusive.

Additionally, no correlation was evident between the number of coaching interventions and reduced absenteeism. Further research could include a prospective analysis of dose-response to coaching visits, which would be of benefit to the disease management industry.

Recommendations

This study has demonstrated the challenges of outcomes-based research in real-life situations. Controlling for confounders, proper data collection, and defining outcomes prior to program implementation certainly would improve the accuracy and validity of program evaluation and can help steer process improvement. As is intuitive to any research, diligence and consistency in data capture are imperative to valid research design.

Since the COK is self-funded, it could require biometric and health screening on all employee members and dependents of its health plan in order for them to receive coverage. This could certainly enhance control group data and allow for samples large enough to perform one-to-one or one-to-two matching. Additionally, asking questions about short-term absence related to chronic disease would likely be an adequate surrogate to administrative data which appear to be flawed in accurately capturing the type of leave members take when addressing their health needs.

In seeking greater improvements in biometric measures, outcome-based incentives could be implemented to drive health improvements, thereby driving down direct and indirect costs. These incentives need to be carefully administered so that they are fair and practical and in compliance with recent regulations released by the Federal government. The current focus of the myHealth Program has been centered on education and awareness as well as disease management services. Environmental focus on wellness has also been shown to heighten employee awareness and improve perceptions of the organization as a healthy place to work.[38] Screening tools could be deployed which assess self-reported absenteeism and then compare the results with administrative data. It may be more cost-effective to use self-reporting absenteeism as well as presenteeism to get a fuller picture of the productivity cost/reduction within the workplace population.

Based on the literature review and the results of the current study, more attention in the workplace needs to be focused on the prevention of chronic disease and their *sequelae* through weight reduction, lifestyle management, and early disease management. Integrating administrative data and productivity data can assist employers in developing effective workplace programs, [39] and, according to Birnbaum *et al*., data integration offers a more balanced approach to wellness and disease management evaluation.[40]

Disease management programs should strive to integrate care planning with the treating physicians to ensure cohesive, team-based care. Patient-centered medical home delivery models have shown improved outcomes when coordinated with primary care providers. Logically, integrating work-based health services and community-based care delivery can improve access to patient care, enhancing compliance to care plans. Enhancing and correlating process measures, such as the number of health coaching visits and the key aspects of disease management offered at coaching visits, could also be used to enhance the efficacy of this intervention.

Lastly, the author agrees with the premise by Goetzel, *et al.*, 2007, in the *Journal of Health Promotion,* that in addition to increasing funding for applied research, experiences and best practices should be shared among colleagues in wellness and disease management. [41]

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Appendices:

Appendix A: Definition of Terms

The terms listed below are used throughout this study and are defined as follows:

ADA	American Diabetic Association
AHA	American Heart Association
Asthma	Reversible inflammatory airway disease
Biometrics	Describes laboratory and other bodily measurements of health (e.g., blood glucose, height, weight.
BMI	Body Mass Index. A number calculated from a person’s weight and height. Used as a surrogate for body fatness. www.cdc.gov/healthyweight/assessing/bmi/).
CAD	Coronary Artery Disease. Macrovascular damage and plaque formation on the coronary arteries that supply blood to the heart.
CHF	Congestive Heart Failure. Failure of the heart to fill and empty properly due to mechanical or electrical abnormalities of the heart.
The Center	The City of Knoxville Health, Wellness, and Education Center
CMPH	Career Masters in Public Health
COK	City of Knoxville
COPD	Chronic Obstructive Pulmonary Disease. Irreversible, obstructive airway disease associated with inflammation, secretion production, and airway contraction. Often associated with chronic tobacco smoking.
DBP	Diastolic Blood Pressure. Arterial pressure measured in mmHg when the heart is at rest.
Disease Management	A system of coordinated health care interventions and communications for populations with conditions in which patient self-care efforts are significant.[1]
DM	Diabetes Mellitus. A complex endocrine disease which is associated with insulin resistance, insulin deficiency causing elevated blood glucose levels. *Sequelae* include micro- and macrovascular damage leading to other disease processes.
DM Type 2	Type of Diabetes Mellitus associated with insulin resistance and later insulin deficiency. Also often called “Adult Onset Diabetes.”

HA1C	Hemoglobin A1c. A laboratory value which correlates with the average blood glucose level over a 2-3 month period of time.
Healthcare 21 Business Coalition	Tennessee coalition of businesses including purchasers, payers, and providers of healthcare whose mission is to improve value-based healthcare delivery and to support businesses in managing their healthcare dollars.
Heart disease	Also called cardiovascular disease and coronary heart disease. – A simple term used to describe several problems related to plaque buildup in the walls of the arteries or atherosclerosis. As the plaque builds up, the arteries narrow, making it more difficult for blood to flow and creating a risk for heart attack or stroke (AHA).
HEDIS	Healthcare Effectiveness Data and Information Set
HTN	Hypertension – high blood pressure
Hyperlipidemia	Elevated blood cholesterol, LDL, and/or abnormal LDL/HDL ratio
Medical Only	Depicts those employees who are not in the myHealth Program, but are on the health plan
MyHealth	The City of Knoxville Wellness Program
NCQA	National Committee for Quality Assurance
Obesity	Having a body mass index above 30 kg/m^2
PCMH	Patient-Centered Medical Home. The healthcare delivery model places the patient in the center of care delivery. Predicated on physician-directed, coordinated care, the PCMH improves access, assures quality, and focuses on team-based care approach
Physical Activity Affidavit	This form must be completed monthly by all myHealth participants attesting they have engaged in rigorous physical activity at least three days a week, every week of the month.
Presenteeism	Practice of coming to work despite illness, injury, or anxiety that often results in reduced productivity
SBP	Systolic Blood Pressure. Maximum arterial pressure measured in mmHg when the heart contracts.
SMG	Summit Medical Group. Physician-owned practice in the East Tennessee region. Predominantly primary care focused, SMG is one of the nation’s largest NCQA-certified, Patient-Centered Medical Homes.

Appendix B: Literature Review

The literature review is focused on the questions “What are the key factors of disease management?”, and “How have various disease management and wellness endeavors affected absenteeism?”

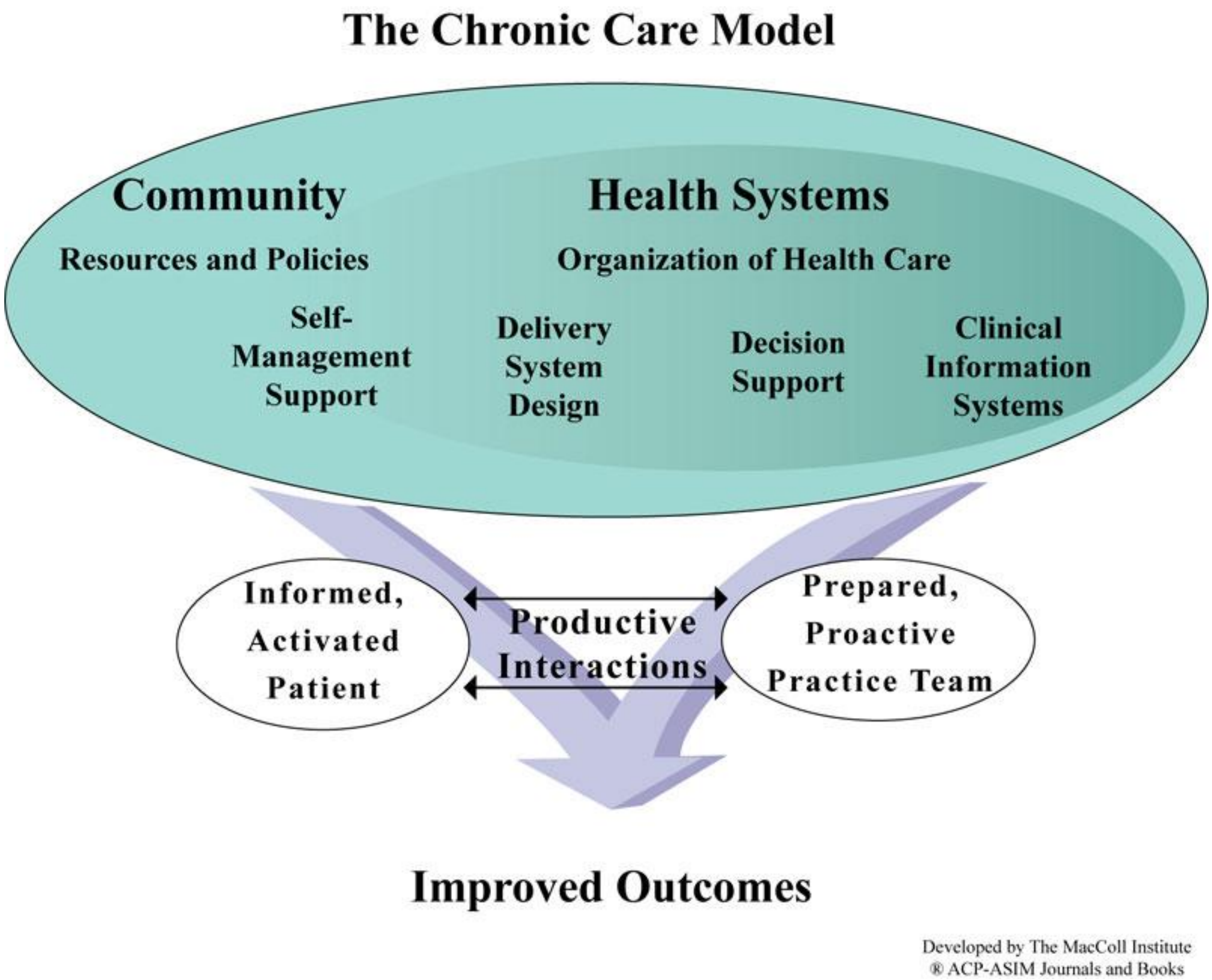
The author performed a PubMed search using the keywords “disease management” (290296), “absence” (43847), “absenteeism” (8691), and “cost claims” (6509) utilizing advanced settings of human, English language, full text available, clinical trials, and reviews.

Combinations are shown in the table below:

Terms	Second Term	Third Term	Totals
Disease Management	Cholesterol		159
Disease Management	Diabetes		550
Disease Management	COPD		94
Disease Management	Asthma		128
Disease Management	HTN		490
Disease Management	Cost Claims		656
Disease Management	Cost Claims	Diabetes	116
Disease Management	Cost Claims	Cholesterol	11
Disease Management	Cost Claims	HTN	40
Disease Management	Cost Claims	Asthma	46
Disease Management	Cost Claims	COPD	31
Disease Management	Cost Claims	Obesity	7
Disease Management	Absenteeism	Diabetes	31
Disease Management	Absenteeism	Asthma	99
Disease Management	Absenteeism	COPD	14
Disease Management	Absenteeism	Cholesterol	10
Disease Management	Absenteeism	CVD	31
Disease Management	Absenteeism	Obesity	15

Titles and Abstracts were reviewed for all of the searches above. Articles that were clearly not relevant to the focus questions were excluded from the library of articles. In addition to the PubMed search, the author searched the *Journal of Occupational and Environmental Medicine* archives for articles related to chronic disease/condition management and "absenteeism" and "claims cost." A total of 142 articles were found that addressed some form of disease/condition management as it relates to claims or absenteeism.

Appendix C: Theoretical Framework



Self-Management Support

Self-management support includes placing the proper knowledge, tools, and resources in the hands of the individuals to allow them to manage their disease. Examples include: face-to-face health coaching and disease management, support groups, quarterly educational seminars, and age-and-literacy appropriate educational materials. For the City of Knoxville population identified with a chronic disease, health coaching/disease management is performed by a certified diabetic educator and/or a registered nurse. The training resources and curriculum are evidenced-based and are a modified version of the Institute for Clinical Systems Improvement's

Health Care Guidelines[14] as well as other evidenced-based guidelines. Support groups are voluntary education and support groups held throughout COK facilities and are available during working hours. Quarterly educational seminars are presented by qualified staff on a variety of topics from preventive care to disease specific care. Educational materials are offered at all of the above venues as well as at the health screening. The promotion of self-awareness and individual responsibility are essential to self-management. Free glucometers and supplies are offered to participants in COK's wellness program along with training on how to operate the equipment.

Delivery System Design

The City of Knoxville delivery system is designed around convenience and access to the employee. Employees are stratified based on: disease burden (number of chronic diseases, severity in terms of disease-related claims dollars) and biometrics. Smokers are also required to engage in health coaching in order to maintain incentives. Participation in myHealth requires: 1.) annual health screening/risk assessment including biometrics, 2.) a monthly physical activity affidavit, 3.) participation in a quarterly health education activity, and 4) health coaching/disease management if risk stratification places the employee in a high risk group. Risk stratification is based on claims cost, biometrics, and risk assessment results. Contingent on the risk stratification, the frequency and intensity of health coaching varies. Health Coaches/Care Managers also assess readiness to change and advise employees about disease- specific programs that may last several weeks (e.g., "Understanding Diabetes," "Smoking Cessation Program," "Pre-diabetes/Metabolic Syndrome"). Extrinsic incentives are other key elements in the My Health Program and include: premium reduction, reduction in cost of chronic medications through a Health Savings account (WageWorks), and a five-dollar copayment for acute care visits at the Center.

Decision Support

Annual reports are analyzed by the Healthcare 21 Business Coalition. These reports drill down to disease-related claims. At an individual level, the disease-related groups (DRGs) are collated with biometrics from the prior year's health screening. Summit Medical Group analyzes real-time biometrics to stratify new employees and to restratify participants on a periodic basis. Monthly reports are generated on those employees who have completed the physical activity affidavits and quarterly educational activities. The Center staff engages employees who have not completed the requirements to obtain the incentives on a monthly basis. *Ad hoc* reports are generated on diabetics, pre-diabetics, and obese employees by department/work status and are used to recruit individuals into various programs and educational classes.

Clinical Information Systems

The wellness vendor uses the Allscripts electronic medical record solution to capture biometrics, certain health screening information, and health coaching/care management visit records. Lab information is directly linked to the EMR via the vendor's Laboratory Information System. Monthly feeds are provided to the Health Plan and Healthcare 21 for processing further reports. Verisk[42] is a data analysis tool that allows individual and group reports on claims dollars and biometrics.

Appendix D: Supporting Data

Table 1. Comparison of Variables of Participants vs. Nonparticipants, Year 0

		Participant (N = 204)	Nonparticipants (N = 115)	p value
Age		N = 203*	N = 113*	<0.01
	Mean (Median)	53.60 (54.00)	48.5 (48.00)	
	Minimum-Maximum	28-67	28 - 65	
Hourly Rate		N = 192**	N = 104**	0.01
	Mean (Median)	22.53 (20.91)	20.49 (18.99)	
	Minimum-Maximum	9.25 - 57.82	12.75 - 42.51	
Annual Rate		N = 192**	N = 104 **	0.14
	Mean (Median)	48,739.74 (45,710.02)	46,083.22 (45,4246.48)	
	Minimum - Maximum	23,002.30 - 120,275.10	27,221.10 - 88,425.10	
Gender		N = 205	N = 115	< 0.01
	Male	153 (74.6%)	107 (93.1%)	
	Female	52 (25.4%)	8 (6.9%)	
Job Category		N = 205	N = 114**	< 0.01
	Fire	34 (16.6%)	35 (30.4%)	
	Gen Government	90 (43.9%)	24 (21.7%)	
	Police	34 (16.6%)	33 (28.7%)	
	Public Service	47 (22.9%)	22 (19.2%)	
Age Range		N = 205	N = 113**	< 0.01
	<35	7 (3.4%)	11 (9.6%)	
	35 - 44	31 (15.1%)	30 (26.1%)	
	45 - 54	65 (31.7%)	35 (30.4%)	
	55 - 64	86 (42.0%)	31 (27.0%)	
	65 of >	15 (7.8%)	6 (7.0%)	
Annual Pay Range		N = 205	N = 115	0.38
	< $20K	13 (6.3%)	11 (9.6%)	
	$ 20K - 29K	7 (3.4%)	7 (6.1%)	
	$30K - 39K	50 (24.4%)	31 (27.0%)	
	$40K - 49K	63 (30.7%)	26 (22.6%)	
	$50 or >	72 (35.2%)	40 (34.7%)	

Table 2. Biometric Comparison of Nonparticipants vs. Participants, Year Zero (2008)

Category	NonParticipant		Participant		P value
	n= 115	%	n=205	%	
BMI Category					< 0.01
Underweight	34	29.6	6	2.9	
Normal Weight	7	6.1	16	7.8	
Overweight	32	27.8	65	31.7	
Obese	26	22.6	65	31.7	
Obese class 2	11	9.6	29	14.2	
Morbidly Obese	5	4.4	24	11.7	
BMI	n = 81		n = 199		0.11
Mean	31.01		32.26		
Median	30.24		31.21		
Min - Max	21.63 -49.78		20.30 - 53.81		
Total Cholesterol	n = 74		n = 161		0.6
Mean	192.01		189.71		
Median	187.25		187.00		
Min - Max	130-306		91-215		
Adjusted for no levels below 90					
LDL Cholesterol	n = 69		n = 157		0.27
Mean	122.06		116.62		
Median	121.00		116.00		
Min - Max	52 - 227		33 - 207		
Fasting Glucose	n = 74		n = 162		0.24
Mean	101.27		107.38		
Median	94.00		95.00		
Min - Max	74 - 228		70-396		
Systolic Blood Pressure	n = 88		n = 201		0.40
Mean	129.01		129.89		
Median	130.00		130.00		
Min - Max	106-160		104 - 189		
Diastolic Blood Pressure	n = 88		n = 201		0.19
Mean	77.79		79.45		
Median	78.00		80.00		
Min - Max	50 - 106		56 - 100		
Absence	n = 111		n = 195		0.03
Mean	8.19		9.41		

Table 3. Claims-driven Disease Burden for Participants vs. Nonparticipants

Variable	Nonparticipants (N = 115)			Participants (N = 205)		Chi Square	P value
Disease Burden	N=	%		N=	%	10.42	0.06
1	20	17.39		23	11.22		
2	47	40.08		65	31.71		
3	36	31.30		72	35.12		
4	9	7.82		34	16.59		
5	3	2.61		8	3.90		
6	0	0.00		0	0.00		
7	0	0.00		3	1.46		
Asthma						0.52	0.47
No	103	89.57		178	86.83		
Yes	12	10.43		27	13.17		
CAD						0.33	0.57
No	108	93.91		189	92.20		
Yes	7	6.09		16	7.80		
CHF						2.48	0.12
No	114	99.13		197	96.10		
Yes	1	0.87		8	3.90		
COPD						0.89	0.34
No	110	95.67		200	97.56		
Yes	5	4.35		5	2.44		
Diabetes						3.29	0.07
No	91	79.13		143	69.76		
Yes	24	20.87		62	30.24		
HTN						1.79	0.18
No	36	31.30		50	24.39		
Yes	79	68.70		155	75.61		
High Cholesterol						0.25	0.62
No	39	33.91		64	31.22		
Yes	76	66.09		141	68.78		

Table 4. Comparison of Continuous Variables by Subgroup

	N	Skew	Mean	Median	Minimum	Maximum
Age						
Fire	69	none	46.78	47	28	65
General Government	115	Right	55.30	57	29	66
Police	67	Right	47.22	46	29	78
Public Service	69	Right	53.32	55	29	66
Annual Pay						
Fire	60	Left	48,942.60	48,604.05	37,128.50	62,843.00
General Government	108	Left	48,543.41	43,098.13	27,722.50	120,275.00
Police	66	Left	54,474.97	52,742.69	38,506.40	83,777.90
Public Service	63	Left	37,723.39	36,532.91	23,002.30	57,454.10
Hourly Pay Rate						
Fire	60	Left	18.08	17.68	12.75	28.31
General Government	108	Left	23.36	20.54	9.25	57.82
Police	66	Left	26.19	25.36	18.51	40.28
Public Service	63	Left	18.14	17.56	11.06	27.62

Table 5. Statistical Change in Biometrics Year-Over-Year for Nonparticipants and Participants

Cholesterol

	Non Participants				Participants		
Years	N	Mean	p value		N	Mean	p value
2011-2008	70	-6.39	0.17		158	-12.06	0.00
2010-2008	69	-8.53	0.04		155	-11.45	0.00
2009-2008	67	-6.24	0.91		155	-6.15	0.02

LDL Cholesterol

	Non Participants				Participants		
Years	N	Mean	p value		N	Mean	p value
2011-2008	60	-10.7	0.03		150	-12.04	0.00
2010-2008	63	-6.83	0.06		150	-9.74	0.00
2009-2008	59	-8.13	0.01		148	-4.61	0.02

Glucose

	Non Participants				Participants		
Years	N	Mean	p value		N	Mean	p value
2011-2008	70	1.21	0.73		158	0.2	0.94
2010-2008	69	1.26	0.64		153	-3.79	0.15
2009-2008	67	0.62	0.75		154	-1.83	0.46

Table 6. Difference in Difference Biometric Analysis Compared to Year 0 (2008)

Category		Nonparticipant	Participant	p value Satterthwaite
Glucose		n = 69	n = 153	
	Year 1	0.62	-1.83	0.44
	year 2	1.26	-3.79	0.18
	Year 3	1.21	0.2	0.82
LDL		n = 70	n = 148	
	Year 1	-8.13	-4.61	0.32
	year 2	-6.83	-9.74	0.5
	Year 3	-10.7	-12.04	0.8
Cholesterol		n = 67	n = 155	
	Year 1	-6.24	-6.16	0.99
	year 2	-8.53	-11.45	0.55
	Year 3	-6.39	-12.06	0.3
BMI		n = 81	n = 199	
	Year 3	0.23	-0.09	0.52
Systolic BP		n = 88	n = 201	
	Year 3	0.25	-1.41	0.45
Diastolic BP		n = 88	n = 201	
	Year 3	0.63	-2.97	0.02
Absence				
	Year 1	0.87	0.07	0.58
	Year 2	0.49	-0.08	0.69
	Year 3	-1.30	-2.04	0.58

Table 7. Mean Changes in Cholesterol Comparing Intervention Years to Year 0

Year 3 to Year 0	Participants				NonParticipants		
	N	Mean	P value		N	Mean	p value
Fire	30	-4.32	0.55		30	-9.85	0.22
General Government	64	-15.69	<0.01		6	-21.17	0.21
Police	33	-16.51	< 0.01		30	-1.92	0.75
Public Service	31	-7.34	0.26		4	8.25	0.79

Year 2 to Year 0	Participants				NonParticipants		
	N	Mean	P value		N	Mean	p value
Fire	29	-5.88	0.39		30	-10.44	0.10
General Government	62	-14.79	< 0.01		7	33.71	0.01
Police	32	-12.25	0.02		28	-2.05	0.72
Public Service	32	-9.24	0.11		4	4.5	0.89

Year 1 to Year 0	Participants				NonParticipants		
	N	Mean	p value		N	Mean	p value
Fire	30	1.02	0.87		30	-13.53	0.01
General Government	65	-13.99	0.01		6	-13.50	0.32
Police	30	-4.54	0.26		27	-1.15	0.78
Public Service	30	2.03	0.66		4	25.00	0.69

Table 8. Mean Change in LDL Cholesterol by Work Group

Year 3 to Year 0	Participants				NonParticipants		
	N	Mean	p value		N	Mean	p value
Fire	28	-8.48	0.21		25	-15.78	0.07
General Government	60	-13.98	< 0.01		6	-14.17	0.22
Police	32	-16.02	< 0.01		26	-3.98	0.55
Public Service	30	-7.23	0.19		3	-19.67	0.32

Year 2 to Year 0	Participants				NonParticipants		
	N	Mean	p value		N	Mean	p value
Fire	28	-6.19	0.34		27	-8.97	0.13
General Government	59	-12.95	< 0.01		7	-20.57	0.01
Police	31	-8.91	0.05		26	0.65	0.91
Public Service	32	-7.74	0.14		3	-20.33	0.21

Year 1 to Year 0	Participants				NonParticipants		
	N	Mean	p value		N	Mean	p value
Fire	28	-1.18	0.82		26	-13.29	0.01
General Government	61	-9.17	0.01		6	-3.33	0.70
Police	29	-4.65	0.21		24	-1.54	0.69
Public Service	30	1.49	0.70		3	-25.67	0.32

Table 9. Mean Difference in Sick Leave by Work Group Compared to Year 0

Year 3	Participants			NonParticipants		
	N	Mean	p value	N	Mean	p value
Fire	19	0.74	0.49	20	1.00	0.55
General Government	76	-4.99	0.01	17	-3.24	0.09
Police	20	-1.80	0.05	23	-4.13	0.07
Public Service	42	-1.45	0.35	18	-1.06	0.81

Year 2	Participants			NonParticipants		
	N	Mean	p value	N	Mean	p value
Fire	24	2.50	0.25	22	0.59	0.41
General Government	77	-1.74	0.27	21	1.14	0.42
Police	22	0.59	0.64	26	-0.15	0.94
Public Service	42	-0.19	0.89	20	-0.45	0.94

Year 1	Participants			NonParticipants		
	N	Mean	p value	N	Mean	p value
Fire	21	0.57	0.43	20	0.45	0.53
General Government	77	-0.51	0.75	20	0.15	0.90
Police	21	3.24	0.22	27	3.41	0.30
Public Service	42	-0.45	0.75	20	-2.20	0.63