Using Predictive Analytics for Early Identification of Short-Term Disability Claimants Who Exhaust Their Benefits

Kara Contreary (corresponding author)
Mathematica Policy Research
505 14th Street, Suite 800
Oakland, CA 94612
Email: kcontreary@mathematica-mpr.com
Tel. (510) 285-4614
Fax: (510) 830-3701

Yonatan Ben-Shalom
Mathematica Policy Research
1100 1st Street, NE, 12th Floor
Washington, DC 20002

Brian Gifford
Integrated Benefits Institute
595 Market Street, Suite 810
San Francisco, CA 94105

Acknowledgement: The authors thank the Integrated Benefits Institute for providing the data, and David Mann and David Stapleton for providing helpful comments on an early draft. The research reported herein was performed pursuant to a grant from the Social Security Administration that was funded as part of the Disability Research Consortium (Grant DRC12000001-04-00). The opinions and conclusions expressed are solely those of the authors and do not represent the opinions or policy of SSA nor of any other agency of the federal government. Neither the U.S. government nor any of its agencies or employees makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this paper.
Using Predictive Analytics for Early Identification of Short-Term Disability Claimants Who Exhaust Their Benefits

Abstract

**Purpose:** Early interventions can help short-term disability insurance (STDI) claimants return to work following onset of an off-the-job medical condition. Accurately targeting such interventions involves identifying claimants who would, without intervention, exhaust STDI benefits and transition to longer-term support. We identify factors that predict STDI exhaustion and transfer to long-term disability insurance (LTDI). We also explore whether waiting for some claims to resolve without intervention improves targeting efficiency.

**Methods:** We use a large database of STDI claims from private employer-sponsored disability insurance programs in the United States to predict which claims will exhaust STDI or transition to LTDI. We use a split sample approach, conducting logistic regressions on half of our data and generating predictions for the other half. We assess predictive accuracy using ROC curve analysis, repeating on successive subsamples, omitting claims that resolve within two, four, and six weeks.

**Results:** Age, primary diagnosis, and employer industry were associated with the two outcomes. Rapid attrition of short-duration claims from the sample means that waiting can substantially increase the efficiency of targeting efforts. Overall accuracy of classification increases from 63.2 percent at week 0 to 82.9 percent at week 6 for exhausting STDI benefits, and from 63.7 percent to 83.0 percent for LTDI transfer.

**Conclusions:** Waiting even a few weeks can substantially increase the accuracy of early intervention targeting by allowing claims that will resolve without further intervention to do so. Predictive modeling further narrows the target population based on claim characteristics, reducing intervention costs. Before adopting a waiting strategy, however, it is important to consider potential trade-offs involved in delaying the start of any intervention.

**Keywords:** disability insurance, predictive analytics, early intervention
Using Predictive Analytics for Early Identification of Short-Term Disability Claimants Who Exhaust Their Benefits

Introduction

Short-term disability insurance (STDI) provides partial wage replacements to employees temporarily unable to work because of off-the-job illness or injury. STDI coverage has grown in the last two decades; 39 percent of private sector workers were covered in 2014, up from 36 percent in 1999, although access and participation rates vary substantially across occupation groups [1].\(^1\) STDI benefits are structured so as to incentivize a return to work as soon as possible. Lost wages are replaced only partially by STDI payments and are typically for a fixed period of time. The median coverage length is six months, although some plans cover a year or more. The median replacement rate is 60 percent, and most plans cap the payment at a maximum benefit amount.

STDI claimants who are not able to return to work before their benefits expire may be at risk of job loss and continued financial support from benefits such as private long-term disability insurance (LTDI) and federal Social Security Disability Insurance (SSDI).\(^2\) However, little is known about factors influencing STDI duration, let alone about the transition from STDI to LTDI or SSDI. On the former topic, Goetzel and colleagues [2] found significant variation in costs associated with STDI across 10 costly and prevalent health conditions; the three costliest conditions were depression/sadness/mental illness, arthritis, and heart disease. Others have found a positive relationship between body mass index (BMI) and claiming STDI benefits [3]; and between age, musculoskeletal disorders, and depression and STDI claim duration [4].

Perhaps more is known about factors influencing work-related disability under workers’ compensation (WC) programs.\(^3\) Stover and colleagues [5] found that predictors of long-term disability among new WC claimants include delay between injury and first medical treatment, older age, back injury, mental disorder, construction industry, smaller firm size, and higher unemployment rate. Sears and colleagues [6] found that injury severity scores based on ICD-9 codes available in WC medical billing data were significantly associated with the duration of work disability and medical cost outcomes. A systematic review of predictive factors for return to work in workers with low back pain identified measures of pain, functional status, and worker’s recovery expectations as important predictors [7]. More recently, several WC-related studies have focused on the positive association between receipt of opioid prescriptions and duration of WC benefits [8]. A recent analysis of LTDI data found that plan characteristics can influence LTDI claims incidence, with shorter waiting periods and higher replacement rates leading to higher incidence; furthermore, higher replacement rates also led to higher incidence of LTDI claims that ultimately led to an SSDI award [9].

---

\(^1\) Five states and Puerto Rico have mandatory STDI benefits; three of those states provide insurance to most workers via public funds: California, New Jersey, and Rhode Island. Hawaii and New York require employers to provide short-term disability benefits through self-insurance or a licensed carrier.

\(^2\) As with STDI, LTDI policies provide wage replacements following a specified duration of disability (often 14, 26, or 52 weeks), up to a maximum benefit duration.

\(^3\) Workers’ compensation covers cash benefits and medical care to workers with work-related (or “on-the-job”) medical conditions. In 46 states and the District of Columbia, employers may either purchase workers’ compensation insurance in a competitive marketplace or self-insure. Four states—North Dakota, Ohio, Washington, and Wyoming—rely exclusively on state workers’ compensation funds.
The first few days and weeks after the onset of a condition that makes it difficult to work are a critical period during which decisions and actions by various stakeholders, including workers themselves, may have major implications for long-term outcomes [10-12]. An STDI claim can be an early point of identification of workers with such conditions, when they are still attached to an employer and may be most likely to benefit from evidence-based health care and other services and supports to prevent their medical conditions from leading to long-term work disability [13]. However, careful timing and targeting of early intervention is critical to efficiency; some workers may return to work without intervention, while others may not benefit from intervention [14]. In both cases, spending resources on early intervention would not result in improved labor force retention.

Accurately targeting early interventions first involves identification of STDI claimants who would, in the absence of intervention, exhaust their STDI benefits and progress to longer-term support. In this paper, we focus on this first step—identifying STDI claimants who are likely to exhaust benefits.\(^4\) We use a large database of STDI claims to estimate a predictive model using characteristics that are observable in STDI claims to predict which claims will reach maximum benefit duration or transition to LTDI.

A key consideration when predicting which claimants will exhaust their benefits is when to make the prediction. Waiting a few days or weeks before attempting to identify likely benefit exhausters can allow some claims to drop from consideration as the claimants return to work after short absences. This process of attrition could potentially make the task of identifying high-risk claims easier. Consequently, we incorporate the timing of the prediction into our analysis.

Thus, we address two primary research questions: First, which observable factors help predict exhaustion of STDI benefits and transfers to LTDI? Second, to what extent can waiting for some claims to resolve without intervention improve the efficiency of targeting STDI claimants for early intervention aimed at helping them remain in the workforce?

We hypothesize that many of the predictors of work disability in WC data will also predict exhaustion of STDI benefits and transfers to LTDI, to the extent they are available in our data. This includes age, back injuries, industry, and firm size. We also expect that certain diagnoses such as mental disorders, various cancers, and chronic diseases that are more prevalent in STDI than WC will be predictive of work disability. Other potential predictors are gender, wage (which determines the level of compensation), and plan characteristics, such as the length of the elimination period. Our data do not include medical information beyond diagnosis or any measures of workers’ return to work expectations.

With regards to waiting before predicting, the elimination of claims that resolve before we attempt to identify likely benefit exhausters will clearly result in a smaller set of claims to potentially target for further intervention. However, it is unclear whether predictive modelling within that smaller set of claims will be more or less accurate than prediction based on the set of all initial claims. Therefore, an important contribution of this paper is our examination of the trade-off between performing a prediction using initial claims that allows for intervening right away (and potentially using a less accurate targeting strategy) and waiting for some claims to resolve before making predictions (which may improve targeting but would necessarily delay intervention, potentially degrading any intervention’s success in returning claimants to work).

**Methods**

\(^4\) Ideally, we would also be able to distinguish between claimants whose labor force participation outcome is responsive to early intervention and claimants who cannot continue to work even with intervention. We do not address this complicated challenge in our paper.
Data

We use Integrated Benefits Institute (IBI) health and productivity benchmarking data from 2011 through 2015. IBI maintains the largest database of employer-based occupational and non-occupational benefits programs in the United States. The data include STDI claims from more than 15,000 private employer-sponsored disability insurance policies in nine U.S. insurance carriers’ and third-party leave administrators’ books of business. Claims from state-run disability insurance programs (such as California’s State Disability Insurance program) are not included. The claims data are collected for leave administration purposes by the carriers and administrators, and include information on claim outcomes, claimant characteristics, employer characteristics, and insurance plan design characteristics.

We limit our analysis to closed STDI claims with a maximum benefit duration of 26 weeks, which was the most common maximum benefit duration in the data. Twenty-six weeks is also one month longer than the SSDI waiting period. Our analytic sample includes 820,751 closed STDI claims from 8,587 small, medium, and large businesses associated with all nine carriers and leave administrators.

We have two outcomes of interest: exhaustion of STDI benefits and transition to LTDI. Exhaustion of STDI benefits indicates that the claimant remained out of work and received benefits for the 26 weeks permitted under his or her employer’s insurance plan. We observe whether the claim reached maximum benefit duration for all claims in our sample. Transition to LTDI indicates that, once the maximum STDI benefit duration was reached, the claimant remained out of work and began receiving LTDI benefit payments. We observe the LTDI transition outcome for only a subset of our sample, from carriers that provided this information for specific employer policies: 559,216 closed claims from 4,659 businesses and four carriers.

For each claim, we also observe individual, employer, and plan characteristics. At the individual level, we observe age, sex, ICD-9 primary diagnosis code, weekly wage, and census division (nine divisions set by the U.S. Census Bureau that we use to capture geographical factors affecting STDI duration). At the employer level, we observe two-digit North American Industry Classification System (NAICS) industry code and the number of covered lives (which we use as a proxy for company size). At the plan level, we observe the elimination period, or the period of time between the first day of work absence following the onset of disability and the date on which benefits begin. For age, ICD-9 code, and industry code, we

5 With the exception of New York, New Jersey, Rhode Island and Hawaii which require that employers provide STDI benefits to workers, in the U.S., disability insurance is provided at an employers’ discretion as an employee benefit. California requires that all employees maintain disability insurance, but does not compel employers to purchase policies on behalf of workers. Whether or not an employer-based policy is state-mandated, the employer typically pays the STDI policy’s premiums if it fully insures through an insurance carrier. Employers may also self-insure, paying the dollar value of all wage replacements costs from its own cash reserves, with or without contracting for administrative services through a third party.

6 Claims with benefit duration of 26 weeks made up 73 percent of the claims in the IBI data. Regression and prediction results were similar for claims with benefit duration of 13 weeks and 52 weeks. We cannot observe reason for claim closure, and therefore cannot distinguish between claims that closed because the underlying condition resolved enough for a return to work and claims that closed for other reasons, such as death or transitions away from the sponsoring employer.

7 It should not be inferred from the lack of LTDI information on a claim that an employer does not have both STDI and LTDI policies for their employees. It may be that STDI and LTDI policies are provided by different entities, hence the data are held by different data suppliers.
group values into higher-level categories.\textsuperscript{8} We Winsorize\textsuperscript{9} weekly wage at 1 percent and log-transform company size.

Analytic methods

We begin our analysis by calculating summary statistics for our sample. We then conduct descriptive analyses to illustrate the rate at which claims resolve on their own.\textsuperscript{10}

For each outcome measure, we estimate a logistic model with the outcomes of interest as the dependent variable and the individual, employer, and plan characteristics as predictors.\textsuperscript{11} We convert regression coefficients to average marginal effects to assess the factors that most strongly predict reaching maximum benefit duration and transitioning to long-term disability. We then generate predicted probabilities for each claim. A concern with predictive modeling is that the function will fit too closely to the data (overfitting), overexplaining idiosyncrasies in the study data and limiting the function’s predictive power outside the sample. To avoid overfitting, we use a split sample approach in which we randomly divide the sample into a modeling half, which is used in the regressions, and a validating half, which is used for generating predictions.

We use receiver operating characteristic (ROC) curve analysis to evaluate the predictive performance of our models. An ROC curve characterizes the trade-off between predictor sensitivity and specificity [15]. Sensitivity captures the true positive rate, or the proportion of cases reaching the specified outcome (say, exhausting STDI benefits) that are flagged as high risk. Specificity captures the true negative rate, or the proportion of cases that do not exhaust STDI benefits and that are correctly classified as not high risk. For each estimated model, sensitivity and specificity depend on the probability threshold used to classify observations. The ROC curve depicts all possible combinations of sensitivity and specificity for that model obtained by varying the threshold from 0 to 1, with sensitivity on the vertical axis and one minus specificity on the horizontal axis. One minus specificity is the false positive rate. A threshold of 0 means all cases are predicted to exhaust their benefits (high sensitivity, low specificity); a threshold of 1 means no cases are predicted to exhaust their benefits (low sensitivity, high specificity). Thus, the ROC curve maps out the incremental trade-off between them (see Figure 2 in the results section).

\textsuperscript{8} We organize diagnoses into the major categories described in the ICD-9. Pregnancy-related claims are excluded. We selected specific subcategories based on relevance to workplace disability. These include back conditions such as intervertebral disc disorders, mental health conditions such as depression and affective disorders, malignant neoplasms, and sprain injuries. Categories of diagnosis that occur very rarely in STDI (such as diseases of the skin, blood, and blood-forming organs, congenital anomalies, and symptoms without a diagnosis) are grouped together as “other illnesses”. Other illnesses account for almost 8 percent of diagnoses, about half of which are undiagnosed symptoms.

\textsuperscript{9} Winsorizing involves setting extreme values to a specified percentile of the data to limit the effect of outliers, which may be spurious; in this case, we set all data below the 1st percentile to the 1st percentile value and all data above the 99th percentile to the 99th percentile value.

\textsuperscript{10} Presumably, some STDI carriers already intervene in some fashion to improve outcomes for claimants on certain employer policies. In that context, “resolve on their own” can be interpreted as “resolve under current practice.”

\textsuperscript{11} We also tested a version of the logistic regression model that included interactions between each age group and each diagnosis category, and a version that also included sex-diagnosis interaction terms. We also tested for nonlinear effects of wage and company size by using wage tercile categories and company size categories (0-5k, 5-10k, 10k+). The results were nearly identical, so we present results from the model with no interaction terms, linear wage, and log of company size.
Although there is no generally accepted rule for optimally trading off sensitivity and specificity in the context of predicting STDI exhaustion and transition to LTDI, there are frameworks for studying predictive power. We adopt a commonly used point on the ROC curve (and the corresponding probability threshold): the point that maximizes the sum of the two, called Youden’s Index [16]. We then calculate a set of measures aimed at illustrating the model’s performance using the threshold indicated by Youden’s Index. The area under the ROC curve (AUC) is a commonly used index for a model’s overall predictive accuracy [17]. An AUC of 1 indicates a model that predicts all outcomes perfectly. A model that is no better than chance has an AUC of 0.5, corresponding to an ROC curve that overlays the diagonal line from (0,0) to (1,1).

To assess how the predictive power of the model changes with time, as some claims resolve and drop out of the sample, we estimate and assess our logistic models four times: once on the full sample and then sequentially eliminating claims that resolved within two weeks, four weeks, and six weeks of benefit start. We then calculate the overall accuracy of an approach that involves waiting for some claims to resolve and then using a predictive model to identify remaining claims that are high risk for exhausting benefits.

**Results**

**Descriptive analysis**

Only a small fraction of closed claims—7.7 percent—exhaust STDI benefits (see columns I and II of Table 1). Claimants who exhausted their benefits were older and less likely to be female. They were also more likely to be from Southern or mid-Atlantic states (not shown). They earned an average of about $40 less per week than those whose claims did not reach the maximum benefit duration. The distribution of primary diagnoses was somewhat different between STDI benefit exhausters and non-exhausters, with exhausters more likely to have cancer (malignant neoplasms), intervertebral disc disorders, other back disease, and mental health disorders (depression and PTSD). Compared to non-exhausters, exhausters are employed by smaller firms and are more likely to work in labor-intensive industries (agriculture, mining, construction, transportation, utilities) and less likely to work in service-oriented industries. Further, their plans tended to have longer elimination periods (not shown). These differences were significant at the 1 percent level.

Of the claims for which we could observe LTDI transition, 6.6 percent made the transition (columns III and IV of Table 1). The differences between beneficiaries who transitioned to LTDI and those who did not were similar to the differences between beneficiaries who did and did not exhaust their benefits in the full sample. The difference in weekly wages was smaller, and the difference in employer size was larger. The distribution of characteristics was similar between the set of claims for which we could observe STDI exhaustion and the subset of claims for which we could observe LTDI transition. Weekly wage was slightly higher in the subset of claims with information on LTDI exhaustion. Table A1 in the appendix provides claim counts for the same set of descriptive characteristics.

---

12 The AUC represents the probability that the predicted value for a randomly chosen positive is greater than the predicted value for a randomly chosen negative.
Table 1. Descriptive statistics for closed claims, by outcome

<table>
<thead>
<tr>
<th>Individual characteristics</th>
<th>STDI Exhaustion (N=820,751)</th>
<th>LTDT Transition (N=559,216)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N=757,250 (92.3%)</td>
<td>N=63,501 (7.7%)</td>
<td>N=521,901 (93.4%)</td>
</tr>
<tr>
<td>Age (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 18-24</td>
<td>2.4%</td>
<td>1.0% **</td>
</tr>
<tr>
<td>Age 25-34</td>
<td>14.7%</td>
<td>8.2% **</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>22.1%</td>
<td>16.3% **</td>
</tr>
<tr>
<td>Age 45-54</td>
<td>29.8%</td>
<td>30.9% **</td>
</tr>
<tr>
<td>Age 55-64</td>
<td>25.9%</td>
<td>36.3% **</td>
</tr>
<tr>
<td>Age 65+</td>
<td>5.1%</td>
<td>7.3% **</td>
</tr>
<tr>
<td>Female (%)</td>
<td>55.1%</td>
<td>49.3% **</td>
</tr>
<tr>
<td>Census division (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>New England</td>
<td>5.2%</td>
<td>4.7% **</td>
</tr>
<tr>
<td>Mid-Atlantic</td>
<td>18.4%</td>
<td>20.3% **</td>
</tr>
<tr>
<td>E. N. Central</td>
<td>18.2%</td>
<td>16.2% **</td>
</tr>
<tr>
<td>W. N. Central</td>
<td>5.6%</td>
<td>4.5% **</td>
</tr>
<tr>
<td>S. Atlantic</td>
<td>21.0%</td>
<td>23.4% **</td>
</tr>
<tr>
<td>E. S. Central</td>
<td>7.3%</td>
<td>6.7% **</td>
</tr>
<tr>
<td>W. S. Central</td>
<td>10.4%</td>
<td>10.4%</td>
</tr>
<tr>
<td>Mountain</td>
<td>6.2%</td>
<td>5.8% **</td>
</tr>
<tr>
<td>Pacific</td>
<td>7.7%</td>
<td>7.8%</td>
</tr>
<tr>
<td>Weekly wage, Winsorized ($)</td>
<td>$1,256.12</td>
<td>$1,216.75 **</td>
</tr>
<tr>
<td>Primary diagnosis (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Musculoskeletal &amp; connective tissue (Not back disease)</td>
<td>15.6%</td>
<td>16.1% **</td>
</tr>
<tr>
<td>Digestive system</td>
<td>10.6%</td>
<td>2.7% **</td>
</tr>
<tr>
<td>Heart &amp; circulatory</td>
<td>6.5%</td>
<td>9.8% **</td>
</tr>
<tr>
<td>Genitourinary system</td>
<td>6.4%</td>
<td>2.1% **</td>
</tr>
<tr>
<td>Malignant neoplasms</td>
<td>4.3%</td>
<td>13.8% **</td>
</tr>
<tr>
<td>Respiratory system</td>
<td>5.7%</td>
<td>2.7% **</td>
</tr>
<tr>
<td>Intervertebral disc disorders &amp; spondylosis</td>
<td>3.8%</td>
<td>7.7% **</td>
</tr>
<tr>
<td>Condition</td>
<td>2011</td>
<td>2012</td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Thoracic &amp; lumbosacral neuritis &amp; radiculitis</td>
<td>3.9%</td>
<td>4.9%</td>
</tr>
<tr>
<td>Depression/affective disorders, PTSD</td>
<td>3.0%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Central &amp; peripheral nervous system</td>
<td>2.5%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Metabolic system</td>
<td>2.2%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Benign neoplasms</td>
<td>2.0%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Eye &amp; ear disorders</td>
<td>1.0%</td>
<td>0.9%</td>
</tr>
<tr>
<td>Other back disease</td>
<td>4.8%</td>
<td>7.0%</td>
</tr>
<tr>
<td>Other mental disorders</td>
<td>4.5%</td>
<td>4.5%</td>
</tr>
<tr>
<td>Other sprains &amp; strains</td>
<td>3.6%</td>
<td>3.3%</td>
</tr>
<tr>
<td>Other injuries</td>
<td>11.2%</td>
<td>9.0%</td>
</tr>
<tr>
<td>Other illnesses</td>
<td>8.4%</td>
<td>7.9%</td>
</tr>
<tr>
<td>Employer characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size (covered lives)</td>
<td>34,387</td>
<td>25,988</td>
</tr>
<tr>
<td>Industry (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture, mining, construction, transportation, utilities</td>
<td>7.0%</td>
<td>11.5%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>30.6%</td>
<td>31.9%</td>
</tr>
<tr>
<td>Wholesale &amp; retail trade</td>
<td>18.1%</td>
<td>17.2%</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>10.7%</td>
<td>7.0%</td>
</tr>
<tr>
<td>Services</td>
<td>31.3%</td>
<td>29.4%</td>
</tr>
<tr>
<td>Public sector</td>
<td>2.3%</td>
<td>2.9%</td>
</tr>
<tr>
<td>Plan characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elimination period (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up to 1 day</td>
<td>14.9%</td>
<td>12.6%</td>
</tr>
<tr>
<td>Up to 1 week</td>
<td>70.4%</td>
<td>68.7%</td>
</tr>
<tr>
<td>Up to 2 weeks</td>
<td>12.9%</td>
<td>15.1%</td>
</tr>
<tr>
<td>More than 2 weeks</td>
<td>1.8%</td>
<td>3.6%</td>
</tr>
</tbody>
</table>

Notes: * p<0.05, ** p<0.01. Statistical significance of differences assessed with Student’s t-test. Table A1 in the appendix provides claim counts for the same set of descriptive characteristics.
Waiting for claims to resolve

One potential strategy for more accurately targeting early intervention efforts is to wait for some claims to resolve on their own. In our sample, a substantial fraction of claims resolved quite quickly. Figure 1 illustrates the rate at which claims resolve after the start of benefits and how the composition of the set of remaining claims becomes “riskier” over time. Dropping claims that resolved within six weeks halves the number of claims under consideration. Correspondingly, the percentage of remaining claims reaching maximum benefit duration (or transitioning to LTDI) increases with time. One would therefore have a smaller pool of claims to attempt to target after allowing short-duration claims to drop from the sample by waiting a few weeks.

Figure 1. Percentage of claims reaching key outcomes, by number of weeks since claim initiation

![Graph showing percentage of claims reaching key outcomes](image)

Predicting which claims exhaust benefits

Factors associated with reaching outcomes. Individual, employer, and plan characteristics were all associated with reaching our outcomes of interest (Table 2). The probability of exhausting STDI benefits increased nearly linearly with age, reaching 6 percentage points higher for ages 55 and over than for ages 18–24. By far the diagnosis most strongly associated with STDI benefit exhaustion was cancer. A diagnosis in the category of malignant neoplasms increased the predicted likelihood of reaching maximum duration by 14 percentage points relative to a diagnosis of “eye & ear disorders” (our reference category). Back pain and mental health disorders, which together constitute a large share of SSDI awards, were also positively associated with exhausting benefits. For diagnoses of “intervertebral disc disorder” and “other back disease,” the probability of exhausting benefits was 8 and 5 percentage points higher, respectively; depression and PTSD were associated with a 6 percentage point increase in probability of STDI exhaustion. Weekly wage was not associated with exhausting STDI benefits. Sex was significantly associated with benefit exhaustion, statistically, but the magnitude of the association was small: Being female reduced the predicted probability of exhausting STDI benefits by 0.7 percentage points. The same set of individual characteristics was associated with transitioning to LTDI with the exception of sex, which was not correlated with that outcome.
Among employer characteristics, industry was strongly associated with the likelihood of STDI exhaustion; for those employed in agriculture, mining, construction, and transportation, the predicted probabilities of reaching maximum duration were 3 to 6 percentage points higher than in other industries. The association was similar for transitioning to LTDI, although the estimated average marginal effects were smaller and in some cases not statistically significant. Employer size was not associated with either outcome.

Finally, the plan’s elimination period was very strongly associated with reaching both of our two outcomes. Relative to elimination periods of one day or less, elimination periods of more than two weeks resulted in a 5 percentage point increase in predicted probability of exhausting STDI benefits or transitioning to LTDI. The elimination period results most likely reflect selection on severity; claimants with conditions that will allow them to return to work quickly may be less likely to file claims if their plans have longer elimination periods. The association of elimination period with reaching our outcomes of interest diminished in regressions that were restricted to claims that had a minimum claim duration of two or more weeks.

**Table 2. Average marginal effects from logistic regression, by key outcome**

<table>
<thead>
<tr>
<th></th>
<th>Reach maximum benefit duration (N=820,751)</th>
<th>Transition to LTDI (N=599,216)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual characteristics</td>
<td>AME</td>
<td>S.E.</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 25-34</td>
<td>0.012***</td>
<td>0.002</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>0.025***</td>
<td>0.002</td>
</tr>
<tr>
<td>Age 45-54</td>
<td>0.041***</td>
<td>0.002</td>
</tr>
<tr>
<td>Age 55-64</td>
<td>0.061***</td>
<td>0.003</td>
</tr>
<tr>
<td>Age 65+</td>
<td>0.064***</td>
<td>0.004</td>
</tr>
<tr>
<td>Female</td>
<td>-0.007**</td>
<td>0.002</td>
</tr>
<tr>
<td>Weekly wage, Winsorized ($)</td>
<td>-0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Primary diagnosis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Musculoskeletal &amp; connective tissue (not back disease)</td>
<td>0.020***</td>
<td>0.003</td>
</tr>
<tr>
<td>Digestive system</td>
<td>-0.033***</td>
<td>0.002</td>
</tr>
<tr>
<td>Heart &amp; circulatory</td>
<td>0.043***</td>
<td>0.003</td>
</tr>
<tr>
<td>Genitourinary system</td>
<td>-0.026***</td>
<td>0.002</td>
</tr>
<tr>
<td>Malignant neoplasms</td>
<td>0.135***</td>
<td>0.005</td>
</tr>
<tr>
<td>Respiratory system</td>
<td>-0.014***</td>
<td>0.003</td>
</tr>
<tr>
<td>Intervertebral disc disorders &amp; others</td>
<td>0.084***</td>
<td>0.004</td>
</tr>
<tr>
<td>Depression/affective disorders, PTSD</td>
<td>0.059***</td>
<td>0.004</td>
</tr>
<tr>
<td>Central &amp; peripheral nervous system</td>
<td>0.055***</td>
<td>0.003</td>
</tr>
<tr>
<td>Metabolic system</td>
<td>-0.006*</td>
<td>0.003</td>
</tr>
<tr>
<td>Benign neoplasms</td>
<td>-0.030***</td>
<td>0.003</td>
</tr>
</tbody>
</table>
### Back sprains & strains

| Back sprains & strains | 0.023*** | 0.004 | 0.012* | 0.005 |

### Other back disease

| Other back disease | 0.053*** | 0.003 | 0.047*** | 0.004 |

### Other mental disorders

| Other mental disorders | 0.039*** | 0.004 | 0.034*** | 0.004 |

### Other sprains and strains

| Other sprains and strains | 0.018*** | 0.003 | 0.014*** | 0.004 |

### Other injuries

| Other injuries | -0.010*** | 0.002 | -0.006* | 0.003 |

### Other illnesses

| Other illnesses | 0.022*** | 0.002 | -0.012 | 0.003 |

### Employer characteristics

- **Log of size (covered lives)**
  - 0.001

### Industry

- **Manufacturing**
  - -0.032*

- **Wholesale & retail trade**
  - -0.038**

- **Finance, insurance, real estate**
  - -0.059***

- **Services**
  - -0.044**

- **Public sector**
  - -0.036*

### Plan characteristics

### Elimination period

- **Up to 1 week**
  - 0.009*

- **Up to 2 weeks**
  - 0.021***

- **More than 2 weeks**
  - 0.048***

**Notes:** * p<0.05, ** p<0.01, *** p<0.001. Regressions also included census division. Omitted categories were: for age “18-24,” for primary diagnosis “eye & ear disorders,” for industry “agriculture, mining, construction, transportation, and utilities,” for elimination period “up to 1 day.”

**ROC curves.** Figure 2 shows the ROC curves generated from the full set of initiated claims. In panel a, which shows the curve for reaching maximum benefit duration, sensitivity is 65.4 percent at the Youden’s Index point (corresponding to a probability threshold of 0.08), and specificity is 63.1 percent. The fact that the ROC curve bows out to the northwest of the diagonal line indicates that the model improves prediction over pure chance (AUC of 0.7). In panel b, which shows the curve for transitioning to LTDI, Youden’s Index corresponds to a probability threshold of 0.07, at which sensitivity is 65.6 percent and specificity is 63.5 percent, and the AUC is also 0.7.

**Figure 2.** ROC curves for reaching maximum benefit duration and transitioning to LTDI, all initiated claims

![ROC curves](image)

**Note:** Points on the ROC curve represent deciles of the probability threshold distribution. The 45° line represents the expected curve when predicting at random (i.e., predicting by chance alone).
Predictive accuracy within minimum duration claim subsets. We noted above that waiting allows for some claims to resolve on their own. Because our outcomes are relatively rare, removing large numbers of short-duration claims from the sample might be expected to improve the model’s predictions on the remaining claims (those that do not resolve quickly). We did not find this to be the case; as we successively eliminated short-duration claims from the regression model sample, predictive accuracy for the remaining claims remained comparable to predictive accuracy for the full set of initiated claims. If anything, the model’s predictive performance decreased as known negatives were dropped from the sample, with the AUC falling to 0.6 for both outcomes.

Overall accuracy of classification

Despite the fact that predictive accuracy within successive subsets of claims that meet minimum duration criteria does not improve, the overall accuracy of classification using an approach that combines waiting with predictive modeling represents a substantial improvement over waiting alone or modeling alone. The fact that the overall accuracy of classification improves as more and more ceased claims get classified as low-risk is not surprising, but the extent to which accuracy improves is important. As shown in Table 3, waiting enables large proportions (more than 50 percent at week 6) of initiated claims to be correctly classified as low risk when they resolve on their own (column II). At least some of those were likely among the claims that would have been targeted by the model in week 0. Waiting therefore serves the function of eliminating false positives from the set of targeted claims.\(^\text{13}\) Even as predictive accuracy of the model for the remaining claims remains constant (column III), the overall accuracy of classification increases from 63 percent at week 0 to 83 percent at week 6 for the outcome of exhausting STDI benefits, and from 64 percent at week 0 to 83 percent at week 6 for the outcome of transitioning to LTDI (column IV). The benefit of waiting comes from the relatively rapid attrition of claims from the sample.

Thus, efficiency of targeting improves substantially with waiting. By week 6, compared to week 0, the model would flag fewer than half the number of claims as high risk, from just under 40 percent of all initiated claims to just under 20 percent (column V). This represents a large decrease in the total number of interventions implied (in our sample, the decrease is from 160,509 to 76,498 claims), which could translate to significant savings. At the same time, waiting until week 6 would approximately double the proportion of true positives (flagged claims that ultimately exhaust STDI benefits or transition to LTDI, column VI), from 13 to 25 percent for the outcome of exhausting STDI benefits, and from 11 to 22 percent for the outcome of transitioning to LTDI.

\(^{13}\) Usual practice may, in fact, include some efforts on the part of insurers and/or employers to resolve STDI claims. In the context of discussions around early intervention, we assume that proposed interventions would be in addition to business as usual, and that the attrition of claims from the sample over time forms the baseline resolution rate.
Table 3. Accuracy of claim classification, by minimum claim duration

<table>
<thead>
<tr>
<th>Minimum claim duration (weeks)</th>
<th>Number (percent) of all claims a correctly classified as low risk by waiting (II)</th>
<th>Number (percent) of remaining claims b correctly classified using probability threshold (III)</th>
<th>Number (percent) of all claims classified correctly, including ceased claims (IV)</th>
<th>Number (percent) of all claims classified correctly, including ceased claims (V)</th>
<th>Number (percent) of flagged claims c that reach outcome (VI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number (percent) of all claims a correctly classified as low risk by waiting (II)</td>
<td>Number (percent) of remaining claims b correctly classified using probability threshold (III)</td>
<td>Number (percent) of all claims classified correctly, including ceased claims (IV)</td>
<td>Number (percent) of all claims classified correctly, including ceased claims (V)</td>
<td>Number (percent) of flagged claims c that reach outcome (VI)</td>
</tr>
<tr>
<td>STDI exhaustion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0 (0)</td>
<td>259,713 (63)</td>
<td>259,713 (63)</td>
<td>160,509 (39)</td>
<td>20,825 (13)</td>
</tr>
<tr>
<td>2</td>
<td>76,589 (19)</td>
<td>211,518 (63)</td>
<td>288,107 (70)</td>
<td>130,699 (32)</td>
<td>20,080 (15)</td>
</tr>
<tr>
<td>4</td>
<td>160,690 (39)</td>
<td>157,325 (63)</td>
<td>318,015 (77)</td>
<td>99,738 (24)</td>
<td>19,448 (19)</td>
</tr>
<tr>
<td>6</td>
<td>225,374 (55)</td>
<td>115,012 (62)</td>
<td>340,386 (83)</td>
<td>76,498 (19)</td>
<td>18,930 (25)</td>
</tr>
<tr>
<td>LTDI transition</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0 (0)</td>
<td>178,292 (64)</td>
<td>178,292 (64)</td>
<td>107,303 (38)</td>
<td>12,325 (11)</td>
</tr>
<tr>
<td>2</td>
<td>54,090 (19)</td>
<td>144,698 (64)</td>
<td>198,788 (71)</td>
<td>85,869 (31)</td>
<td>11,796 (14)</td>
</tr>
<tr>
<td>4</td>
<td>112,523 (40)</td>
<td>102,963 (61)</td>
<td>215,486 (77)</td>
<td>69,693 (25)</td>
<td>11,980 (17)</td>
</tr>
<tr>
<td>6</td>
<td>157,895 (56)</td>
<td>74,765 (61)</td>
<td>232,660 (83)</td>
<td>51,868 (19)</td>
<td>11,562 (22)</td>
</tr>
</tbody>
</table>

a All claims indicates all initiated claims, regardless of their final disposition.
b Remaining claims indicates claims that have not resolved by the minimum claim duration week.
c Flagged claims indicates claims that are designated as high-risk by the predictive model.

Discussion

Early intervention efforts require careful timing and targeting to efficiently support workers who are at risk for exiting the labor force. We present a basic model that demonstrates that waiting even a few weeks could potentially increase the accuracy of early intervention targeting efforts that use claim characteristics to model the likelihood of STDI exhaustion and LTDI transition. Waiting allows claims that will resolve without further intervention to do so, and modeling narrows the target population, reducing the costs of intervention. It is not surprising that the overall accuracy of claim classification improves as more and more ceased claims get classified as low-risk, but establishing the extent to which accuracy improves is important. Our findings suggest that accuracy substantially improves by waiting just a few weeks, with implications for early intervention programs aimed at helping workers with medical conditions to remain in the labor force.

However, two considerations warrant caution before adopting a waiting approach to early intervention. First, the value of waiting may be limited if delaying the start of any intervention prolongs work absence and reduces the likelihood of ultimately returning to work. Second, strategies that involve waiting should be developed with consideration for the success rate of the proposed early intervention over time. If the intervention is less effective with individuals who have been out of work for several weeks than for individuals who are only days into their claim, waiting may not improve the efficiency of early intervention programs.

Therefore, in developing an early intervention strategy, it is important to consider the features of the intervention under consideration to gauge the trade-off between intervening right away (and potentially
using a less accurate targeting strategy) and waiting (which may improve targeting but may degrade the intervention’s success in returning claimants to work). For interventions that are costly but have a high success rate, such as well-implemented cognitive behavioral treatment [17-19], it is particularly important to target them efficiently to avoid unnecessary expenditures. Interventions that are less costly, such as mailers designed to “nudge” workers or their health care providers [20-21], can be implemented earlier, when targeting is more difficult but individuals have been out of work for less time. Matching the targeting approach to the proposed intervention can help improve the return on investment.

As an alternative to waiting, if it is possible to collect additional information on claimants—that is, beyond what is observable in their STDI claims—it may be possible to improve targeting without waiting. As mentioned by Neuhauser and colleagues [4], it is possible to improve early predictions by collecting additional data from claimants through psychosocial screener questionnaires designed specifically to predict long-term outcomes.

Similar to Stover and colleagues who examined WC claims in Washington [5], we found that predictors of long-term disability include older age, back injuries, mental disorders, and working in the construction industry. However, smaller firm size was not associated with STDI benefit exhaustion or transition to LTDI in our data when controlling for other factors, and female gender was negatively associated with STDI benefit exhaustion. Neuhauser and colleagues [4], who analyzed both WC and STDI in California, also identified older age, back injuries, and mental disorders as predictors of long-term disability. In addition, they found that female gender was associated with shorter STDI durations but longer WC durations.

We had hypothesized that firm size would predict exhaustion of STDI benefits and transfers to LTDI. The descriptive results indeed indicate a negative association between firm size and these outcomes—the average firm size is smaller for claimants who exhaust their STDI benefits and transfer to LTDI than for those who do not. The fact that firm size was not found to be a significant predictor of long-term disability in the regression analysis suggests that other factors that differ between relatively smaller and larger firms, such as industry and diagnosis, account for the overall difference in outcomes. Notably, this finding differs from Stover and colleagues [5]. A potential explanation for the differing findings is that the WC data include a broader range of firm sizes than the STDI data because WC is mandatory for virtually all firms while STDI coverage is more likely to be offered by larger firms. It may also be the case that firm size is more important in WC than STDI. For example, larger firms may have a stronger financial incentive and greater capacity than smaller firms to help workers who claim WC benefits return to work. One reason firm size may make less of a difference in helping STDI claimants return to work is that WC benefits include health care but STDI benefits do not; this means that employers and their insurers have more options to implement strategies to improve return-to-work outcomes in WC cases.

The strength of this paper’s approach is that it uses a large data set of private STDI claims and commonly used and well-understood predictive accuracy metrics. However, our work has limitations. The most important limitation concerns the number of predictors available in claims data. With additional information (such as from screener questionnaires or medical claims), our predictive model would likely be much more accurate. Thus, it appears that much can be gained in terms of understanding the nature of work disability, the potential for job retention, and the need for early intervention from inclusion of more information about workplace and health factors in routine data collection by disability insurance carriers. For example, it would be helpful to include a measure of the severity of the medical condition, which is known to be associated with the duration of work disability [6].

Our specification of the full model is also very basic, with all terms entering linearly; although adding age-diagnosis and sex-diagnosis interaction terms did not improve the results, it is possible that a still more complex model could improve predictive accuracy. In future work, we hope to use machine learning
techniques such as Random Forest and elastic nets [22-23] to identify constellations of characteristics that are more highly predictive of STDI exhaustion or LTDI transition. Finally, we focus on predicting outcomes that may be related to continued reliance on benefits, but reaching these outcomes is only one characteristic that drives early intervention approaches. We do not attempt to assess which beneficiaries are most likely to benefit from an early intervention, which is also important for early intervention targeting efforts.

Additionally, our metrics of predictive accuracy treat sensitivity and specificity as equally important. However, in the context of early intervention to promote labor force retention, it is unlikely that false positives (providing treatment to someone who does not need it or will not benefit from it) and false negatives (failing to intervene with someone who could benefit) are equally important. Which one is more heavily weighted depends on a number of factors, including the cost of the intervention, its effectiveness over time, and the costs associated with progressing to LTDI or SSDI. Nevertheless, we use these measures here because of their prevalence in the literature and to focus attention on how classification is improved by waiting and by using all available information.

**Conclusion**

Age, primary diagnosis, and employer industry are predictive of STDI benefit exhaustion and transition to LTDI. Waiting even a few weeks can substantially increase the accuracy of early intervention targeting by allowing claims that will resolve without further intervention to do so. Predictive modeling further narrows the target population based on claim characteristics, implying a reduction in potential intervention costs. Before adopting a waiting strategy, however, it is important to consider potential trade-offs involved in delaying the start of any intervention.
Compliance with Ethical Standards

Funding: The research reported herein was performed pursuant to a grant from the Social Security Administration that was funded as part of the Disability Research Consortium (Grant DRC12000001-04-00).

Conflict of Interest: Contrary, Ben-Shalom, and Gifford declare that they have no conflicts of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References


### Appendix

**Table A1. Counts for closed claims, by outcome**

<table>
<thead>
<tr>
<th></th>
<th>STDI Exhaustion (N=820,751)</th>
<th>LTDI Transition (N=559,216)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Claims that do not exhaust STD (I)</td>
<td>Claims that exhaust STD (II)</td>
</tr>
<tr>
<td>N=757,250</td>
<td>N=63,501</td>
<td>N=521,901</td>
</tr>
</tbody>
</table>

**Individual characteristics**

**Age**

- Age 18-24
  - STDI Exhaustion: 18,115
  - LTDI Transition: 623
  - Total: 11,961
  - Claims with transition: 290

- Age 25-34
  - STDI Exhaustion: 111,617
  - LTDI Transition: 5,210
  - Total: 75,317
  - Claims with transition: 2,971

- Age 35-44
  - STDI Exhaustion: 167,307
  - LTDI Transition: 10,363
  - Total: 114,616
  - Claims with transition: 5,992

- Age 45-54
  - STDI Exhaustion: 226,011
  - LTDI Transition: 19,599
  - Total: 157,337
  - Claims with transition: 11,610

- Age 55-64
  - STDI Exhaustion: 195,826
  - LTDI Transition: 23,056
  - Total: 136,513
  - Claims with transition: 13,907

- Age 65+
  - STDI Exhaustion: 38,374
  - LTDI Transition: 4,650
  - Total: 26,157
  - Claims with transition: 2,545

**Gender**

- Female
  - STDI Exhaustion: 417,485
  - LTDI Transition: 31,310
  - Total: 282,742
  - Claims with transition: 18,542

**Census division**

- New England
  - STDI Exhaustion: 39,481
  - LTDI Transition: 2,984
  - Total: 22,101
  - Claims with transition: 1,632

- Mid-Atlantic
  - STDI Exhaustion: 139,518
  - LTDI Transition: 12,905
  - Total: 94,187
  - Claims with transition: 6,491

- E. N. Central
  - STDI Exhaustion: 137,843
  - LTDI Transition: 10,296
  - Total: 100,743
  - Claims with transition: 6,108

- W. N. Central
  - STDI Exhaustion: 42,071
  - LTDI Transition: 2,860
  - Total: 26,658
  - Claims with transition: 1,677

- S. Atlantic
  - STDI Exhaustion: 158,893
  - LTDI Transition: 14,890
  - Total: 111,900
  - Claims with transition: 9,311

- E. S. Central
  - STDI Exhaustion: 55,023
  - LTDI Transition: 4,263
  - Total: 38,915
  - Claims with transition: 2,671

- W. S. Central
  - STDI Exhaustion: 79,131
  - LTDI Transition: 6,617
  - Total: 57,744
  - Claims with transition: 4,284

- Mountain
  - STDI Exhaustion: 47,265
  - LTDI Transition: 3,702
  - Total: 32,602
  - Claims with transition: 2,233

- Pacific
  - STDI Exhaustion: 58,025
  - LTDI Transition: 4,984
  - Total: 37,051
  - Claims with transition: 2,908

**Weekly wage, Winsorized ($)**

- STDI Exhaustion: $1,256.12
- LTDI Transition: $1,216.75
- Claims without transition: $1,378.39
- Claims with transition: $1,386.30

**Primary diagnosis**

- Musculoskeletal & connective tissue (Not back disease)
  - STDI Exhaustion: 117,848
  - LTDI Transition: 10,245
  - Total: 83,488
  - Claims with transition: 6,251

- Digestive system
  - STDI Exhaustion: 80,172
  - LTDI Transition: 1,714
  - Total: 57,515
  - Claims with transition: 1,041

- Heart & circulatory
  - STDI Exhaustion: 49,217
  - LTDI Transition: 6,213
  - Total: 33,878
  - Claims with transition: 3,520

- Genitourinary system
  - STDI Exhaustion: 48,579
  - LTDI Transition: 1,330
  - Total: 35,292
  - Claims with transition: 767

- Malignant neoplasms
  - STDI Exhaustion: 32,857
  - LTDI Transition: 8,765
  - Total: 21,731
  - Claims with transition: 5,197

- Respiratory system
  - STDI Exhaustion: 43,168
  - LTDI Transition: 1,730
  - Total: 29,888
  - Claims with transition: 968
<table>
<thead>
<tr>
<th>Condition</th>
<th>Claims Count</th>
<th>1st Year</th>
<th>2nd Year</th>
<th>3rd Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intervertebral disc disorders &amp; spondylosis</td>
<td>28,972</td>
<td>4,873</td>
<td>20,468</td>
<td>3,012</td>
</tr>
<tr>
<td>Thoracic &amp; lumbosacral neuritis &amp; radiculitis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression/affective disorders, PTSD</td>
<td>29,547</td>
<td>3,093</td>
<td>17,680</td>
<td>1,874</td>
</tr>
<tr>
<td>Central &amp; peripheral nervous system</td>
<td>22,472</td>
<td>2,669</td>
<td>14,759</td>
<td>1,545</td>
</tr>
<tr>
<td>Metabolic system</td>
<td>18,554</td>
<td>883</td>
<td>13,420</td>
<td>502</td>
</tr>
<tr>
<td>Benign neoplasms</td>
<td>16,729</td>
<td>366</td>
<td>12,306</td>
<td>229</td>
</tr>
<tr>
<td>Eye &amp; ear disorders</td>
<td>15,264</td>
<td>938</td>
<td>10,054</td>
<td>570</td>
</tr>
<tr>
<td>Back sprains &amp; strains</td>
<td>7,727</td>
<td>588</td>
<td>4,971</td>
<td>287</td>
</tr>
<tr>
<td>Other back disease</td>
<td>36,180</td>
<td>4,433</td>
<td>23,095</td>
<td>2,556</td>
</tr>
<tr>
<td>Other mental disorders</td>
<td>34,386</td>
<td>2,856</td>
<td>20,889</td>
<td>1,635</td>
</tr>
<tr>
<td>Other sprains &amp; strains</td>
<td>27,454</td>
<td>2,091</td>
<td>19,453</td>
<td>1,259</td>
</tr>
<tr>
<td>Other injuries</td>
<td>84,524</td>
<td>5,716</td>
<td>56,796</td>
<td>3,215</td>
</tr>
<tr>
<td>Other illnesses</td>
<td>63,600</td>
<td>4,998</td>
<td>46,218</td>
<td>2,887</td>
</tr>
<tr>
<td><strong>Employer characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size (covered lives)</td>
<td>34,387</td>
<td>25,988</td>
<td>19,742</td>
<td>34,257</td>
</tr>
<tr>
<td><strong>Industr</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture, mining, construction, transportation, utilities</td>
<td>52,636</td>
<td>7,296</td>
<td>36,645</td>
<td>4,272</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>231,906</td>
<td>20,287</td>
<td>175,811</td>
<td>12,796</td>
</tr>
<tr>
<td>Wholesale &amp; retail trade</td>
<td>136,884</td>
<td>10,934</td>
<td>103,274</td>
<td>6,155</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>81,263</td>
<td>4,447</td>
<td>32,088</td>
<td>2,400</td>
</tr>
<tr>
<td>Services</td>
<td>236,990</td>
<td>18,687</td>
<td>169,383</td>
<td>11,105</td>
</tr>
<tr>
<td>Public sector</td>
<td>17,571</td>
<td>1,850</td>
<td>4,700</td>
<td>587</td>
</tr>
<tr>
<td><strong>Plan characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Elimination period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up to 1 day</td>
<td>112,966</td>
<td>8,023</td>
<td>87,859</td>
<td>4,073</td>
</tr>
<tr>
<td>Up to 1 week</td>
<td>532,754</td>
<td>43,647</td>
<td>369,008</td>
<td>26,911</td>
</tr>
<tr>
<td>Up to 2 weeks</td>
<td>97,654</td>
<td>9,561</td>
<td>57,912</td>
<td>5,399</td>
</tr>
<tr>
<td>More than 2 weeks</td>
<td>13,876</td>
<td>2,270</td>
<td>7,122</td>
<td>932</td>
</tr>
</tbody>
</table>