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Worth the Wait? Improving Predictions of Prolonged Work Disability

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Prompt services and supports can help short-term disability insurance (STDI) claimants return to work after the onset of a medical condition that did not develop on the job. To efficiently target these early interventions to the right people, it is important to identify the claimants who would, without intervention, exhaust their STDI benefits and transition to longer-term support. We use a large database of STDI claims to estimate models that predict who will exhaust STDI and transfer to long-term disability insurance (LTDI). We first assess the potential advantages of waiting for some claims to resolve on their own as a way to narrow the set of claims used to predict who will exhaust STDI benefits or transition to LTDI. We then estimate predictive models four times: first on the full set of claims (as benefits begin), then on those claims that remained after two, four, and six weeks. We estimate the predictive models using half of our data, then generate predictions for the other half to assess the models' performance. Even without modeling, waiting just a few weeks for some claims to resolve on their own can substantially increase targeting accuracy. Modeling after the waiting period narrows the target population even further, thereby improving efficiency. Before adopting a waiting strategy, however, it is important to consider the trade-offs involved in delaying the delivery of special services to claimants who could benefit from early interventions.

Introduction

The last two decades have seen growth in short-term disability insurance (STDI) coverage for employees who are at least temporarily unable to work because of an illness or injury they experienced off the job, although access to this coverage and participation in it vary substantially

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depending on the employee's occupation (Monaco 2015). To incentivize people to return to work as soon as possible, STDI payments provide only partial wage replacement, typically for a fixed period of time. The median coverage length is six months, the median wage replacement rate is 60 percent, and most plans cap the payments at a maximum benefit amount (Monaco 2015). STDI claimants who are not able to return to work before their benefits expire may be at risk of losing their job and eventually requiring income support from programs such as private long-term disability insurance (LTDI)—if they have coverage—or Social Security Disability Insurance (SSDI).

Data and Methods

We use Integrated Benefits Institute health and productivity benchmarking data from 2011 through 2015, which include administrative data on STDI claims from the books of business of nine disability insurance carriers and third-party leave administrators, representing more than 15,000 U.S. employers' disability policies. We limit our analysis to closed STDI claims with a maximum benefit duration of 26 weeks—the most common maximum benefit duration in the data—and estimate a logistic model with the outcomes of interest (exhaustion of STDI benefits, transition to LTDI) as the dependent variable and individual, employer, and plan characteristics as predictors. (We observe the LTDI transition outcome for only a subset of claims from carriers that provided this information for specific employer policies.) Using a split-sample approach, we conduct logistic regressions on half of our data, generate predictions for the other half, and assess the predictive performance of our model. 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 the predictive performance of our logistic models four times: once on the full sample (that is, at zero weeks) and then after sequentially eliminating claims that resolved within two, four, and six weeks.

Little is known about the factors that influence how long a person collects STDI, nor about the transition from STDI to LTDI or SSDI. More is known about the factors associated with long claim duration in workers' compensation (WC) programs that cover cash benefits and medical care to workers with work-related medical conditions (developed as a consequence of being on the job). For example, Stover and colleagues (2007) examine patterns in new WC claimants and find that predictors of long-term disability include a delay between an injury and the first medical treatment; older age; back injury; smaller firm size; and a higher unemployment rate.

STDI claims occur at a critical period during which decisions and actions by various stakeholders, including the workers themselves, may have major implications for long-term outcomes (Franklin et al. 2013; Loisel and Anema 2013; Shaw et al. 2013). Information included in STDI claims could help us identify, early in that critical period, workers who could benefit from interventions intended to get them back to work. However, carefully timing and targeting early intervention is critical if the practice is going to be efficient; some workers may return to work without needing any intervention, whereas others may not benefit from intervention (Stapleton et al. 2015).

An important first step in effectively targeting early interventions to those who might benefit from them is identifying which STDI claimants are, in the absence of intervention, at high risk of exhausting their STDI benefits and progressing to longer-term support. In this brief, we present findings from an analysis based on STDI claims data to estimate models that predict which claims will reach maximum STDI benefit duration or transition to LTDI. Waiting a few days or weeks before attempting to identify people who are likely to exhaust their benefits allows some claimants to drop from consideration as they return to work after short absences, so we also incorporated the timing of the model's prediction into our analysis.

Which STDI claimants exhaust their benefits and transition to LTDI?

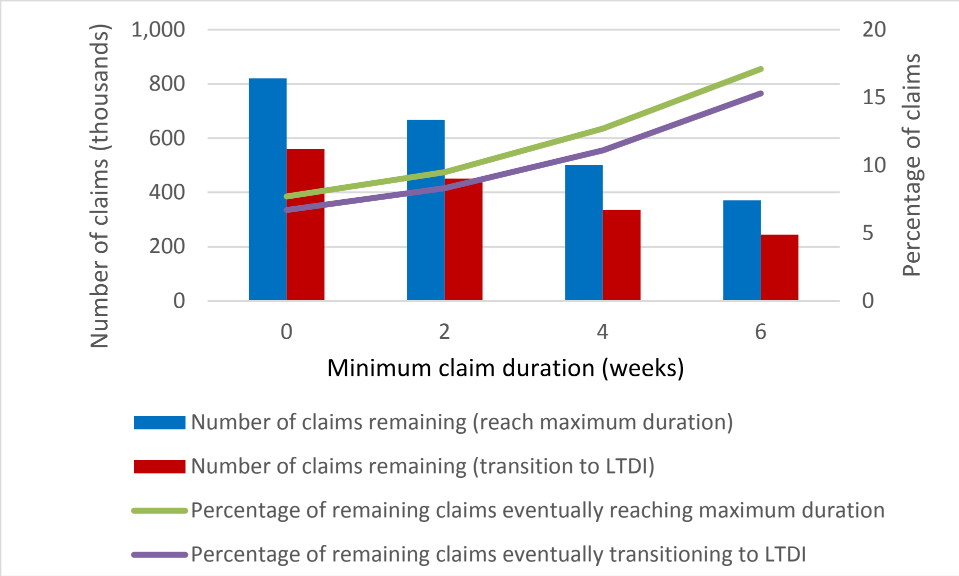
We first examined the differences between the claims of workers who exhaust their STDI benefit or transition to LTDI and those who do not. Only a small fraction of claims—7.7 percent—result in exhausting STDI benefits. Compared to people who do not exhaust their benefits, claimants who exhaust their benefits are older, more likely to be male, and earn an average of about $40 less per week. They are also more likely to be from Southern or mid-Atlantic states, employed by smaller firms, and to work in labor-intensive industries such as construction, transportation, and utilities. The distribution of primary diagnoses is somewhat different depending on whether or not a person exhausts STDI benefits, with those who do exhaust them more likely to have cancer (malignant neoplasms), intervertebral disc disorders, other back diseases, and mental health disorders such as depression and post-traumatic stress disorder (PTSD). Of the claims for which we can observe LTDI transition, 6.6 percent make that transition. When we look at the differences between STDI claimants who transition to LTDI and those who do not, we find patterns similar to those we find in looking at the differences between STDI claimants who do and do not exhaust their benefits. This is expected given the heavy overlap between the two groups of claimants.

At what rate do claims resolve on their own?

Next, we examine what would happen if we allowed time for some claimants to drop out on their own, thereby eliminating people who would not be candidates for exhausting benefits and allowing us to zero in on those who could be. Figure 1 illustrates the rate at which claims in our data are resolved and how the composition of the remaining claims is made up of more and more “benefit exhausters” over time. For example, the overall sample begins with 820,751 claims. Of those, 667,721 (81 percent) were active at least two weeks. Narrowing the focus to claims that are active at least 6 weeks halves the number of claims under consideration. Correspondingly, the percentage of remaining claims that ultimately reach maximum benefit duration (or transition to LTDI) increases with time. The implication for case management is that waiting a few weeks for less serious claims to resolve on their own focuses attention on a smaller pool of claims, which allows more effective targeting of likely STDI benefit exhausters.[1]

[1] Presumably, some STDI carriers already intervene in some fashion to improve outcomes for claimants covered by certain employer policies. In that context, “resolve on their own” can be interpreted as “resolve under current practice.”

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



Which individual, employer, and plan characteristics are associated with exhausting STDI benefits or transitioning to LTDI?

We estimated predictive models four times: first on the full set of claims, then on those claims that remained after two, four, and six weeks. The individual, employer, and plan characteristics associated with STDI benefit exhaustion and transition to LTDI are similar all four times. Here, we describe findings from the model estimated on the full set of claims (that is, at zero weeks).

The probability of exhausting STDI benefits increases nearly linearly with age, reaching a difference of 6 percentage points between people age 55 and over (who have the higher probability) and people age 18–24. This is a large difference considering that just 7.7 percent of claimants overall exhaust their STDI benefits. Cancer is, by far, the diagnosis most strongly associated with STDI benefit exhaustion. A diagnosis in the category of malignant neoplasms increases the predicted likelihood of reaching maximum duration by 11 percentage points relative to a diagnosis of “other illnesses” (our reference category). Back pain and mental health disorders, which together constitute a large share of SSDI awards, are also positively associated with exhausting benefits. Weekly wages are not associated with exhausting STDI benefits. Being female is *negatively* associated with benefit exhaustion—a 0.7 percentage point decrease compared to being male. The same individual characteristics—except gender, which is not correlated—are associated with transitioning to LTDI.

The employer’s type of industry is strongly associated with the likelihood of exhausting STDI benefits. For those employed in agriculture, mining, construction, transportation, and utilities, the predicted probability of reaching maximum duration is 3 to 6 percentage points higher than it is for workers in other industries. Again, these are large differences considering that just 7.7 percent of all claimants exhaust their STDI benefits. The association is similar for transitioning to LTDI, although the estimated effects are smaller. Employer size is not associated with either outcome.

Finally, the STDI plan's elimination period—the period of time between the first day a person is absent from work after the onset of a disability and the date on which benefits begin—is 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 the predicted probability of exhausting STDI benefits or transitioning to LTDI. This finding most likely reflects that 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.

How predictive is our model, accounting for the timing of the prediction?

Finally, to assess how the predictive power of the model changes with time as some claims resolve and drop out of the sample, we compared the predictive performance of the model at weeks 0, 2, 4, and 6. As shown in Table 1, waiting before estimating the predictive model enables a large proportion of claims to resolve on their own (more than 50 percent at Week 6) and thereby be correctly classified as having low risk of benefit exhaustion (Column I). Waiting therefore serves the function of eliminating false positives from the set of targeted claims. Even as predictive accuracy for the remaining claims remains relatively flat (Column II), the overall predictive accuracy for the full set of claims (that is, including those that resolved on their own) increases from 63.2 percent at Week 0 to 82.9 percent at Week 6 for the outcome of exhausting STDI benefits, and from 63.7 percent at Week 0 to 83.0 percent at Week 6 for the outcome of transitioning to LTDI (Column III).

The efficiency of predictive modeling improves substantially with a waiting period enforced before analyzing the sample. By Week 6, compared to Week 0, the model would flag half the number of claims as high risk, from just under 40 percent of all claims to just under 20 percent (Column IV). This represents a large decrease in the total number of claimants identified for potential intervention (in our sample, the decrease is from 160,507 to 76,516 claimants), which could translate to significant savings. At the same time, waiting until Week 6 would double the number of true positives (flagged claims that ultimately exhaust STDI benefits or transition to LTDI, Column V).

Table 1. Predictive performance of model, by minimum claim duration

Minimum claim duration	Percentage of claims correctly classified as low risk by waiting (I)	Percentage of remaining claims correctly classified using probability threshold (II)	Percentage of all claims categorized correctly (III)	Percentage of claims flagged for early intervention (IV)	Percentage of flagged claims that reach outcome (V)
STDI exhaustion					
0 weeks	0.0	63.2	63.2	39.1	13.0
2 weeks	18.6	63.3	70.2	31.8	15.4
4 weeks	39.1	63.0	77.4	24.3	19.5
6 weeks	54.8	62.1	82.9	18.6	24.7
LTDI transition					
0 weeks	0.0	63.7	63.7	38.3	11.5
2 weeks	19.3	64.0	71.0	30.7	13.7
4 weeks	40.1	61.5	76.9	24.9	17.2
6 weeks	56.3	61.2	83.0	18.5	22.3

Discussion

In this brief, we present a basic model that demonstrates how waiting even a few weeks before targeting claims for early intervention could increase the accuracy of models that use claims characteristics to predict the likelihood of STDI exhaustion and LTDI transition. Waiting before estimating the predictive model gives claims that will resolve on their own the time to do so, and modeling further narrows the target population, reducing the costs of any intervention. However, caution is warranted before adopting a waiting approach to early intervention for two reasons. First, the value of waiting before modeling may be offset if delaying the start of any intervention prolongs work absence and reduces the likelihood of ultimately returning to work. Second, the proposed early intervention's success rate over time needs to be taken into consideration. If the intervention is less effective with people who have been out of work for several weeks than it is for people who are only days into their claim, waiting may not improve the efficiency of early intervention.

Thus, in developing a strategy for targeting early intervention, it is important to consider the features of the intervention under consideration and gauge the trade-off between intervening right away (and potentially using a less accurate targeting strategy) and waiting before modeling (which may improve targeting, but may degrade the intervention's success in returning claimants to work). To avoid unnecessary spending, it is particularly important to efficiently target interventions that are expensive but have a high success rate, such as well-implemented cognitive behavioral treatment (Van der Klink et al. 2007; Richmond et al. 2015; Reme et al. 2015). Interventions that are cheaper, such as mailers designed to "nudge" workers or their health care providers (Srivastava 2012; Sacarny et al. 2016) can be implemented earlier, when targeting is more difficult but people have not been out of work long. Matching the targeting approach to the proposed intervention can help improve the return on investment.

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