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A Competing Risk Decomposition of the Average Duration Effect of a 50% cut in Unemployment Benefits[1]

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Abstract

In 2009 the Irish government cut the unemployment benefit paid to 18 year olds from €204 to €100. In this paper, I evaluate the contribution of competing risks to the overall difference in average durations between the treatment and control groups. I propose a decomposition, which is valid irrespective of the dependence structure across exit states or the shape of the underlying hazards. The decomposition distinguishes between incidence and duration effects and provides an intuitive visual representation of these effects. In aggregate, the cut resulted in a substantial reduction in unemployment durations, with the aggregate effect similar across genders. However, the competing risk decomposition reveals substantial gender differences in the response to the cut For men the cut had little impact on the relative proportions exiting to alternative states, however those subjected to the benefit cut exited to all states more quickly. For women however, in addition to the duration effect, the cut also had a substantial effect on exit states, with women subjected to the cut much more likely to exit to work and less likely to exit to inactivity.

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1. Introduction

Ireland was one of the countries worst affected by the Great Recession, with the unemployment rate rising from 4.5% in 2007 to 12.2% in 2009 and peaking at 15% in 2012. While no age group was spared the effects of the Great Recession, younger workers were hardest hit. In response to increasing youth unemployment, in 2009 the Irish government took a decision to substantially reduce unemployment benefit for those aged 18 and 19. For those affected by the cut, weekly benefits fell from €204.30 to €100. Doris et al. (2017) use a regression discontinuity approach to evaluate the impact of this cut on unemployment and find that those subjected the cut had significantly shorter unemployment durations. However, the aggregate effects reported in that paper did not 0examine the relative importance of different exit states.

To examine the importance of alternative exit states one must consider how to deal with competing risks; a competing risk is an event whose occurrence prevents the occurrence of another outcome. For instance, in the medical literature if the outcome of primary interest is time to death due to cardiovascular causes, then a subject dying of cancer can no longer be at risk of dying from a cardiovascular related issue. Austin and Fine (2017) provide a recent survey of competing risks in the medical literature. They conduct an overview of published randomised controlled trials with survival outcomes and find that the majority of these studies were potentially subject to competing risks, a feature not accounted for in the statistical analysis.

Likewise competing risks may be important when analysing unemployment durations. Unemployment spells can end for many reasons, including exits from the labour force, exits to a job (full/part-time) or exits to training and modelling competing risks may have important policy implications. Unemployment durations that end because the claimant moves from unemployment assistance to an alternative welfare payment or leaves the labour force, may be less desirable than unemployment spells that end because the claimant finds a job (van den Berg et al. 2017). However, in keeping the medical literature most of the analysis in labour economics has tended to focus on aggregate effects.[2]

When spells can end for a variety of reasons, researchers and policy makers may wish to understand the impact of competing exits on the overall effect. The typical approach in labour economics is to estimate competing risk hazard functions (Han and Hausman 1990, Narendranathan and Stewart 1993). However, estimation of these models typically imposes strong assumptions on the dependence structure across exit states. In addition, cause specific hazards may be inappropriate for the question at hand. Cause specific hazards allow researchers to estimate the effect of a covariate on the rate of occurrence of an outcome in the subset of people who are event free, but are less useful when one is interested in the effect of a covariate on the absolute risk of the outcome over time (Austin et al. 2016).

In this paper, I extend the previous work on competing risks by proposing a new decomposition that focuses on the differences in durations between two groups. The new approach decomposes the overall difference in durations into the contributions of distinct exit states and is valid irrespective of the dependence structure across exit states. The decomposition has an intuitive visual representation and builds on the Cumulative Incidence Function previously used in competing risk analysis. I also derive an extended version of the decomposition that distinguishes between the duration and incidence effects of a programme. I use this decomposition to re-exmaine the labour market response of 18 year olds jobseekers in Ireland to the 50% cut in unemployment benefits introduced in in 2009. Although the aggregate effect of the benefit cut is similar across

[2] For example none of the studies surveyed by Tatsiramos and van Ours (2012) explicitly account for competing risks.

genders, the decompositions show that the channels through which the benefit cut affects labour supply differs substantially for males and females.

The outline of the paper is as follows. Section 2 provides a very brief overview of previous work on unemployment benefit and duration, before discussing the competing risk approach to duration analysis in more detail, distinguishing between distinguishing between the competing risk hazard approach and cause specific cumulative incidence approach. Section 3 derives the new decomposition and shows how it relates to existing approaches. Section 4 introduces the application used to illustrate the decomposition, namely the impact of the 50% cut in unemployment benefit for young claimants introduced in Ireland in 2009 and section 5 outlines the administrative data used to evaluate this cut. Section 6 provides the results of the decomposition focusing on gender differences in response to the cut and Section 7 concludes.

2. Literature Review

Doris et al. (2017) recently evaluated the impact of a substantial reduction in unemployment benefits on unemployment duration for 18 year old claimants. Using a Regression Discontinuity approach they find that the cut substantially reduced unemployment duration, with an implied benefit elasticity close to 1. This finding is consistent with estimates previously reported in the literature. Tatsiramos and Van Ours (2014) provide a recent summary of this work, with most of the estimates cited ranging between 0.5 and 1.0 for the elasticity of duration with respect to benefits. However, these aggregate effects do not examine the contribution of differences in exit states on duration.

When unemployment spells can end for multiple reasons (e.g. a job, a training course, an education course) a competing risks framework is required. A competing risk is an event whose occurrence precludes the occurrence of another event. One cannot observe people who exit unemployment to training also terminating the same spell with an exit to work. When fitting regression models in the presence of competing risk data, researchers can choose to model the effect of the regressors on the cause-specific hazard or on the Cumulative Incidence Function (CIF).

The use of cause-specific hazards allows one to estimate the effect of covariates on the rate of occurrence of a specific outcome in the subset of the population who are event free at the specified time. This is the common approach to modelling competing risks in labour economics (Heckman and Honore 1989, Edin 1989, Katz and Meyer (1990), Han and Hausman 1990, Narendranathan and Stewart (1991, 1993), Pudney and Thomas 1995, Dolton and O'Neill 1996, McVicar 2008 and van den Berg et al. 2017). In these studies competing risks are typically modelled in terms of a set of latent random variables, each latent variable representing the time to failure from a given cause. The observed data then includes the smallest of the latent variables and the cause of failure. While the cause specific hazards are identified in this approach, neither the joint distribution of the latent or the marginal survival are identified. Cox (1962) showed that for any joint distribution of latent failure times across states, there exists a corresponding joint distribution with independent failure times, which gives rise to the same data generating process. Therefore, in the absence of regressors, the latent variable competing risk hazard approach is not identified without parametric restrictions. Heckman and Honore (1989) show that, in a model with regressors, it is sometimes possible to identify the joint distribution of failure times in a continuous time model without distributional assumptions; the main identifying assumption with single spell data requires that the effect of regressors differ across exit states. However, this restriction cannot be tested using observable data.[3]

To recover the joint and marginal distributions of the latent variables requires the researcher to think about the dependence structure across the latent variables. One possibility is to assume the competing states are independent. The independence assumption means that at a given time, t, subjects who remain at risk of exit to state k, have the same future risk for the occurrence of event k as those who have exited to other states by time t; exits to competing risks are non-informative about exits to the risk of interest. However, in the biomedical literature, independent risks are considered unlikely (Austin et al. 2016). The same is likely true when analysing unemployment durations. For instance, in his analysis of the Hartz labour market reforms in Germany, Price (2016) distinguishes between exits to regular jobs and exits to mini-jobs, a legally distinct class of low paid, part-time jobs and argues that exits to these states are unlikely to be independent. He argues that exits to these states may be either complements (if some claimants receive more job offers across the board) or substitutes (if searching for a regular job crowds out search effort for mini-jobs).

Even when when competing exit states are independent, naïve estimators based on the single cause specific hazards are unlikely to have a useful probabilistic interpretation (Putter et al. 2007, Austin et al. 2016, Varadhan et al. 2010). To see this consider basing estimates of the probability of having failed from cause k by time t on 1-$S_k(t)$, where $S_k(t) = \exp(-\int_0^t \lambda_k(s)\, ds)$ and λ_k is the cause specific hazard. $S_k(t)$ is identified under independent risks and one might

[3] For a discussion of some of some of these identification issues see Heckman and Honore (1989), Han and Hausman (1990), Omori (1998) and Kalblfeisch and Prentice (2002).

consider estimating the probability of having failed from cause k by time t as one minus the Kaplan-Meier estimator based only on exits due to cause *k*, treating all other exists as independently censored. It is straightforward to rewrite 1-$S_k(t)$ as $\int_0^t \lambda_k(s)S_k(s)ds$; simply integrate the latter using integration by parts However, the probability that an event of type k has actually occurred by time *t*, the Cumulative Incidence Function of event *k* ($\mathrm{CIF_k}$), is given by

$$CIF_k = \int_0^t \lambda_k(s)S(s)ds$$

where $S(t) = \exp\left(-\sum_{k=1}^{K}\left[\int_0^t \lambda_k(s)\, ds\right]\right)$ and is the probability of not having failed from *any* event as of time t. Since $S(t) \leq S_k(t)$, it is clear that the naïve estimator based only on the cause-specific hazard for event *k*, treating exit to other states as censored, will overestimate the cumulative incidence of an event in the presence of competing risks, even when the risks are independent.[4] For the naïve estimator to have a meaningful probabilistic interpretation one must think of a world in which the competing events do not occur (Austin et al 2016).

In addition to the problems associated with the naïve estimator, the effect of a covariate on the cause-specific hazard function may be very different to its effect on the likelihood of exiting due to that cause. As noted above, the likelihood of having left due to cause *k*, by time *t*, is given by the cumulative incidence function for cause *k*, which in turns depends on *all* the cause specific hazards. Consequently, the effect of any given covariate on the likelihood of exiting due to cause *k*, will be affected indirectly by the effect of the covariate on all competing causes. In general, it is difficult to deduce the sign of a covariate effect on the CIF directly from the cause-specific hazard

[4] For further discussion of this and other issues that arise with competing risks see Andersen et al. (2002, 2012).

parameters (Kyyra 2009). A covariate may have a strong effect on the cause-specific hazard but no effect on the cumulative incidence.

For these reasons Coviello and Bogges (2004) and Austin and Fine (2017) recommend, that that when competing risks are present, the appropriate estimate of the probability of failure from a specific cause (cause-specific incidence) requires the specification and estimation of the cumulative incidence function or the associated sub-distribution hazard. Fine and Gray (1999) discuss how estimates of the sub-distribution hazard can be used to determine the effect of covariates on the cause-specific cumulative incidence function under the assumption of a proportional hazard model for the sub-distribution.

A small number of recent papers in biostatics have proposed competing risk decompositions of life-expectancy, distinguishing between causes of death (e.g. Beltran-Sanchez et al. (2008) and Vaupel and Canudas-Romo (2003). However, as noted in Andersen et al. (2013) neither of these proposed measures are additive, while the former also requires independence of causes. Andersen (2013) proposes an alternative decomposition based on the areas under the cause–specific cumulative incidence functions. The terms in this decomposition can be interpreted as the expected number of life-years lost due to each cause before a specified date. The Andersen decomposition is additive and does not require independence. However, as I will show in the next section, analysis based solely on the areas under the cumulative incidence can be confounded by differences in prevalence rates of the competing events.[5]

Although the analysis of CIFs is common in the biostatistics literature (Varadhan et al. 2010) it has rarely featured when modelling unemployment durations. Exceptions include Lo and

[5] For a related discussion of this issue see Huang et al. (2016)

Wilke (2010) and Lo et al. (2017), who combine estimated cumulative incidence functions with a parametric copula, to estimate the marginal distribution of latent durations in the presence of competing risks; durations that would be observed in the absence of competing risks. However, in this work estimation of the CIFs is simply a necessary first stage that is required in order to recover the underlying latent marginal distributions; the CIFs themselves are not of primary interest. Price (2016) uses both cause-specific hazards and the cumulative incidence functions to model the effect of the Hartz labour market reform on unemployment durations in Germany. He argues that in order to assess how shifts between full-time and part-time jobs impact estimated wages post-reform, what matters are not the hazard rates, but rather how these rates translate into the share of claimants who eventually end up in each state.

In the remainder of this paper, I extend the previous work on competing risks by proposing a new competing risks decomposition of differences in average duration between groups. The new approach decomposes the overall difference in durations between two groups into the contributions of distinct exit states and like Andersen (2013) is valid irrespective of the dependence structure across exit states or the shape of the underlying CIFs. Furthermore the new approach permits an extended decomposition that distinguishes between differences in durations, conditional on an exit state, and differences in the prevalence of exits to particular states. When prevalence rates are equal across groups our decomposition is equivalent to the decomposition proposed by Andersen (2013). However, when incidence rates differ, the decomposition proposed in this paper captures both duration and incidence effects. This extension is particularly useful if some exit states are seen as more desirable than others are, as is often the case when modelling unemployment duration.

3. Competing Risk Decomposition

In this section, I examine the contribution of competing exit states to the overall difference in mean duration between two groups. I decompose the overall duration effect into state specific components, which can be written as simple functions of the CIF. The decomposition is easy to implement and does not require independence across exit states. I also present a visual representation of the decomposition that helps understand the contribution of differences in the timing of exits across states to the overall duration effect.

I define the treatment effect as the difference in average duration between the treated group and the control group, as would be the case with random assignment (LaLonde 1986, Bloom et al. 1997, Dolton and O'Neill, 2002, van den Berg et al. 2006). Specifically, the treatment effect is

$$\Delta Y = E[Y_T] - \quad E[Y_C]$$

where Yi is the random variable representing the duration of unemployment for group i=T,C, with upper bound T_{Mi}. Let $T_M = max\{T_{Mi}\}$ and for exposition we assume that all spells are completed and identify T_M by the maximum duration observed.[6] The competing risk model has K possible exit states, and we denote the overall proportion of group i exiting into each of the K states by f_{ki}. In our analysis the groups consist of a treatment group, $i=T$, subjected to the treatment and a control group, $i=C$, who did not receive the treatment. By definition of the cumulative incidence function for state k and group i, (CIF_{ki}), it follows that $f_{ki} \equiv CIF_{ki}(T_M)$ and in the absence of censoring $\sum_k \{f_{ki}\} = 1$.

[6] I will discuss extensions to censored durations in the next section.

The starting point of our analysis is the cause-specific decomposition proposed by Andersen (2013). He showed that the mean duration effect can be rewritten as

$$\Delta Y = \sum_k \left\{\int_0^{T_M} \{CIF_{kC}(y) - CIF_{kT}(y)\}\, dy\right\} \qquad (1)$$

Andersen's (2013) decomposition measures the cause specific contribution to differences in durations by the differences in the areas under the cause specific Cumulative Incidence Functions. However, as noted by Huang et al. 2016, analysis based solely on the areas under the cumulative incidence can be confounded by differences in the prevalence rates of the competing events across groups. When analysing the contributions of exits to work to changes in unemployment durations it will often be important to distinguish between the impact of a programme on the duration of time before an exit to a specific state (duration effect) and its impact of the proportion of people moving to different states (incidence effect). This is not possible with the aggregate decomposition, which in turn can cause difficulty for policy makers. For instance with the aggregate decomposition given in (1) it would not be possible to distinguish between a programme that resulted in fewer people moving to work but resulted in those who did move moving more quickly and a programme that had no effect at all on either duration or incidence of people moving to work. We propose an extension of the aggregate decomposition given in (1) that tackles these issues by further decomposing the aggregate effect into a duration effect and an incidence effect. We provide an intuitive interpretation of the individual components and in keeping with Andersen (2013) we show that the decomposition permits a visual presentation of the duration effect in terms of the areas under cumulative incidence functions.

To do this reconsider the overall decomposition

$$\sum_k \left[\left\{ \int_0^{T_M} \{CIF_{kC}(y) - CIF_{kT}(y)\}\, dy \right\} \right]$$

This can be rewritten as

$$\Sigma_k \left[\left\{ \left(\underbrace{f_{kT} \left\{ \left[T_M - \int_0^{T_M} \left[\left[\frac{(CIF_{kT}(y))}{f_{kT}} \right] dy \right] \right] - \left[T_M - \int_0^{T_M} \left[\left[\frac{(CIF_{kT}(y))}{f_{kT}} \right] dy \right] \right] \right\}}_{duration\ \ effect} \right) \right\} + \right.$$

$$\left. \underbrace{\{f_{kT} - f_{kC}\} \left[T_M - \int_0^{T_M} \left[\frac{(CIF_{kT}(y))}{f_{kT}} \right] dy \right]}_{incidence\ \ effect} \right] \quad (2)$$

Furthermore, we can show that $\left[T_M - \int_0^{T_M} \left[\left[\frac{(CIF_{kT}(y))}{f_{kT}} \right] dy \right] \right] = \quad E(Y_T | K_T = k)$.[7]Denoting $\left[\frac{(CIF_{kT}(y))}{f_{kT}} \right]$ as a conditional cumulative incidence function (CCIF; see Huang et al. 2016) we can write $E(Y_T | K_T = k) = \left\{ T_M - \int_0^{T_M} [CCIF_{kT}(y)] dy \right\}$ or $\int_0^{T_M} [CCIF_{kT}(y)] dy = T_M - E(Y_T | K_T = k)$. Thus in the same way that Andersen (2013) shows that the area under the unconditional CIF can be interpreted as the days lost due to cause *k*, we see that the area under the *conditional* cumulative incidence function as the days lost *conditional on exiting to state k.*

Combining the fact that $E(Y_i | K_i = k) = \left\{ T_M - \int_0^{T_M} \left[\frac{(CIF_{kT}(y))}{f_{kT}} \right] dy \right\}$ with equation (2) allows us to rewrite the decomposition as

[7] For proof of this see Appendix 1.

$$\sum_k \left[\underbrace{\langle f_{kT}\{[E(Y_T|K_T = k)] - [E(Y_C|K_C = k)]\}\rangle}_{duration\ \ effect} + \underbrace{\langle\{f_{kT} - f_{kC}\}[E(Y_C|K_C = k)]\rangle}_{incidence\ \ effect} \right] \quad (3)$$

Written in this way it is clear that the first term of the extended decomposition measures the duration effect of state *k*, weighted by the incidence in the treatment group. If the overall incidences are the same for the control and treatment group, $f_{kT} = f_{kC}$, then all of the state *k* effect, will be captured by the conditional duration term, with a negative contribution denoting quicker exits to a given state. The second term measures the incidence effect, weighted by average duration for group *C*.[8] Clearly if the average duration, conditional on being in state *k*, is the same for both groups, but more of the treatment group enter state *k*, then the first term will be zero; all of the state *k* effect will be picked up as a *positive* contribution in the incidence term. How one interprets this component depends on the desirability of alternative states. When exit states are seen as desirable (e.g. work) then s positive (negative) incidence effect reflects well (poorly) on a programme. The opposite is true for exist states that are considered undesirable (e.g. exits into inactivity).

Some further manipulation allows us to rewrite the duration effect as

$$f_{kT}\{[E(Y_T|K_T = k)] - [E(Y_C|K_C = k)]\} = \left\{\int_0^{T_M} \omega_k[CIF_{kC}(y)]dy - \int_0^{T_M}[CIF_{kT}(y)]dy\right\}. \quad (4)$$

where $\omega_k = \frac{f_{kT}}{f_{kC}}$. Thus in the same way that Andersen (2013) shows that the unconditional difference in durations due to cause *k*, can be represented as the difference in the areas underneath the cause specific cumulative incidence functions, rewriting the duration effect in this way shows

[8] As with all decompositions of this type, one can obtain an alternative decomposition by reversing the weightings.

that, in a similar fashion, the conditional duration effect due to cause k, can be represented as the difference in *rescaled* cumulative incidence functions, where the scaling factor for the control group is simply ω_k.

4. Application: Changes to Unemployment Benefit

To illustrate the above decomposition I re-evaluate a cut to unemployment benefits in Ireland in 2009. The social welfare system in Ireland is divided into three main types of payments; social insurance payments, means-tested payments, and universal payments. Jobseeker's Allowance (JA) is a means tested payment that is paid indefinitely to those who are unemployed provided the claimant continues to meet conditions of eligibility. To receive JA a claimant must satisfying the means test, be aged between 18 and 66, be unemployed and actively seeking work.

In response to the fiscal crisis that occurred in Ireland with the onset of the Great Recession, the Irish government imposed substantial cuts on JA payments for young claimants. Prior to 2009, all claimants were entitled to €204 a week. In May 2009, claimants aged 18 and 19 had their weekly rate cut to €100. The fact that the cuts only applied to new claimants allows us to identify a control group, those aged 18-19 who entered unemployment just before the legislation. The behaviour of this group can be compared to those entering just after the legislation to determine the effect of the benefit cut.

Doris et al. (2017) analysed these cuts in detail using a Regression Discontinuity design and found a substantial significant duration effect for 18 year old claimants. However, given that the stated motivation for these cuts was to "ensure that young people are better off in education, employment or training than claiming,"[9] it seems appropriate to consider the relative role of alternative exit states in explaining these aggregate effects. In the remainder of this paper, I apply the decomposition outlined in Section 3, to further evaluate this benefit cut. To allow for possible differences in the response of the benefit cut by gender, I carry out the analysis separately for males and females.

5. Data

To carry out the analysis I use the Longitudinal Jobseekers Database provided by the Department of Social Protection. This is an administrative data set covering every claimant who has received a jobseekers or one parent family payment since 2007. The data provide administrative records for the start and end date of every new claim since January 2007, allowing us to establish both the exact start date and duration for the entire population of new JA claims initiated between 2007 and 2014. Throughout the analysis, I measure duration in months.

When considering the competing risks model, I consider five different exit states; training, work, education, inactivity and "other". Table 1 provides summary statistics for our control and treatment groups by gender. The first row reports the average unemployment duration. For all four groups average unemployment duration exceeded one year, highlighting the poor labour market prospects faced by youths in Ireland during the Great Recession. A comparison of the control and treatment groups shows that, for both men and women, those who entered in May 2009, and were subject to the 50% cut in JA, had unemployment durations that were on average 7 months shorter

[9] http://www.welfare.ie/en/pressoffice/Pages/pr231013.aspx

than those entering in April.[10] This is in keeping with the significant causal effect reported in Doris et al. (2017). The next five rows of Table 1 provide the proportion of each group exiting to each of the alternative states. Looking at men, we see that three exit states dominated; namely training, work and “other”. Furthermore, the proportions across each state are similar for the control and treatment groups. This suggests that the aggregate duration effect for men is driven by differences in duration conditional on a given exit state. The third column shows that the proportions leaving to each state for 18 year old women subjected to the lower benefit are similar to those for men and dominated by the same three exit states. However, for women in receipt of the higher benefit the pattern is notably different. For this group, there is a uniform distribution across exit states, driven by a bigger proportion exiting to inactivity and education, at the expense of those exiting to work. While the results in column 2 and 3 suggest that differences in state specific durations are the driving force behind the male effect, the results in columns 4 and 5 suggest that differences in incidences may play a larger role for women. In the remainder of the paper, I use the decomposition outlined in Section 3 to examine these issues more formally.

6. Results

The results of the basic decompositions are given in Table 2. The overall treatment effect presented in the first row is based on a comparison of those entering unemployment in the month

[10] In our application approximately 4% of observations are censored. In the results discussed here censored observations are omitted from the analysis. It is relatively straightforward to extend the decomposition to account for censoring (see Appendix 2). In this case the average duration effect can be interpreted in terms of restricted mean differences (see for example Royston and Parmar (2013)). Because of the small number of cases that are censored, controlling for censoring makes little difference in our application. For instance, the mean duration effect for men is -30 weeks when censored observations are omitted, -34.8 when censored observations are treated as complete and -34.88 when censoring is accounted for.

before the legislation and those entering in the month after. As noted earlier we see a large and statistically significant response to the benefit cut for both men and women. The aggregate effect is very similar across genders; those subjected to the benefit cut have unemployment durations that are over 7 months shorter than those in receipt of the higher benefit. This implies a benefit duration elasticity of .67 for both genders.[11]

The remaining rows of Table 2 show the contributions of the competing exit states to the overall effect. Looking at the results for males, we see that no single exit state dominates the overall effect. While the contribution of exits to education and inactivity are small, the other three exit states, training, work and "other", all contribute a substantial component to the overall effect. The shorter overall duration for 18 year old males is therefore a result of shorter durations to each of these three states.

Although the overall aggregate effect for women is very similar to the male effect, the decomposition results show that this effect is generated through very different channels. While exits to work is the dominant factor for men, it appears to contribute the least to the female duration effect. In contrast, exits to inactivity, which are not important for men, is the dominant channel for women. The fact that very similar aggregate effects for men and women, operate through very different channels, highlights the value of the competing risk decomposition developed in this paper.

The results of the extended decomposition are given in Table 3 and Figures 2 and 3. Table 3 provides the estimates for both the duration and incidence effects, while Figures 2 and 3 provide

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[11] Using a Regression Discontinuity approach, Doris et al. (2017) estimate a somewhat larger duration benefit elasticity of 1.0 for this group of claimants.

the graphical representation of the duration effect. Looking at the duration effect for men, we see that, conditional on exiting to a given state, those in receipt of the lower benefit exited quicker than those in the control group. This is particularly true for the three main effects identified earlier; training, work and “other”. This is illustrated graphically in Figure 2, where for each of these three exit states the rescaled CIF for the control group lies below the CIF of the Treatment group.

The incidence effect shows, that for men, differences in the likelihood of exiting to a given state are less important. The fact that the work incidence effect for men is negative implies that members of the treatment group are *less likely* to exit to this state. Since work is likely to be considered a desirable state, this negative incidence effect would be viewed as an undesirable outcome. However, it is smaller than the duration effect, which sees treated men exit more quickly to work. Competing duration and incidence effects, such as these, are not possible under the proportional hazard assumption typically assumed in the literature. If members of the treatment group are more likely to exit to a state during the early part of their spell, then the proportional hazards assumption requires that this must be true at every duration. Proportional hazard models therefore restricts the duration and incidence effect to operate in the same way, a restriction that is violated in our example.

Overall, the male results suggest that the incidence effect is relatively unimportant for men; what matters for men is the timing of the exits to each of the states. The same is not the case for women. Looking at the duration effects, we see that the results are quite similar to those reported for men. Conditional on exiting to that state, those in receipt of the lower benefit exit quicker than those in the control group. This is particularly true for work where the duration effect is larger for women than for men. However, in addition to the conditional duration effect, the fact that the work incidence effect is *positive* and large for women implies that women who are subject to the benefit cut are *more* likely to enter work. Both of these work effects would be considered desirable but they offset each other in the aggregate decomposition.

The importance of distinguishing between duration and incidence effects for women is also evident when we consider exits to inactivity. Although there is little difference in the timing of exits to inactivity for women in the treatment and control groups, the large negative effect in the inactivity incidence column shows that women subject to the benefit cut are much *less* likely to exit to inactivity. Since exits to inactivity are likely to be considered an undesirable outcome, this additional effect of the benefit cuts would be welcomed.

Exits to inactivity for women can also be used to illustrate the value of our extended decomposition. The left-hand panel of Figure 3 compares the raw CIF functions for the treatment and control groups for this state, as suggested by Andersen (2013). Such a comparison clearly yields substantial differences between the two groups. While the differences in incidences are obvious in this graph, as noted earlier it is not possible from this comparison alone to distinguish between duration effects and incidence effects. The right hand panel reproduces the graph for the *conditional duration* effect using the decomposition developed in this paper. Since these two curves are very similar, we can conclude that the overall effect observed in the right hand panel is driven entirely by the incidence component.

In summary, while the overall initial response to the benefit cut is very similar for men and women, the decomposition reveals differences in the channels through which men and women respond to the benefit cut. For men the response primarily took the form of quicker exits to all of the destination states, with little effect on the overall incidence across states. For women however, we observe both a conditional duration effect and a substantial incidence effect. The benefit cut resulted not only in women moving into work more quickly, but also in more women choosing to move into work rather than inactivity. Although the focus of this paper is on the initial duration of unemployment, the estimated differences in the relative importance of incidence effects by gender suggest that the long-run effects of the benefit cuts may differ by gender. The benefit cut may have a long-run effect for men in so far as the shorter unemployment durations reported for these men reduces the potential scarring effects associated with unemployment. However, the resulting change in the distribution of claimants across exist states for women may result in additional long run effects over and above those normally associated with reduced scarring.

7. Conclusion

When dealing with duration data researchers must confront how to deal with competing risks. If the primary outcome of interest is the exit rate to a given state then one could estimate a cause-specific hazard. For those interested in the overall incidence of exits to different states then cause-specific hazards are insufficient and by themselves are likely to give misleading results. In such cases, researchers rely on estimating Cumulative Incidence Functions. In this paper, I consider how to deal with competing risk when the outcome of interest is the difference in average duration between two groups. To examine this question, I propose a competing risk decomposition, which identifies the contribution of each exit state to the overall difference in duration between the two groups. I also develop an extended decomposition that distinguishes between differences in duration conditional on an exit state and differences in the incidence of exits to each state.

I illustrate the decomposition by examining the impact of a 50% cut to unemployment benefit for 18 year-old claimants in Ireland. I consider the effect separately for men and women. For both genders, the aggregate effect of the benefit cut reduces unemployment duration by approximately seven months. However, the competing risk decomposition reveals substantial gender differences in the channels through which this effect operated. For men, the treatment has little impact of the relative proportions exiting to each state. Instead, those subject to the benefit cut exit to all states quicker. This is particularly true of the exits to training, to work and to "other" states. I find similar duration effects for women, particularly for exits to work and to "other" states. However, for women, the benefit cut also has a significant impact on the relative incidences across states. Those subject to the benefit cut are much more likely to exit to work and less likely to exit to an inactive state. The additional incidence effects apparent for women indicate another channel through which the benefit cut effects behaviour for young women. This additional channel may have important policy implications, implications that are only evident following the competing risks decomposition.

Table 1: Summary Statistics by Control and Treatment Status state

	18 year old Males		18 year old Females	
	Treatment	Control	Treatment	Control
Average unemployment Duration (months)	15.03	22.56	13.83	20.75
Proportion exit to Training	.35	.31	.31	.30
Proportion exit to Work	.31	.36	.36	.21
Proportion exit to Education	.05	.06	.06	.11
Proportion exit to Other	.26	.25	.20	.19
Proportion exit to Inactive	.03	.03	.06	.18
N	428	378	297	211

Table 2: Competing Risk Decomposition (Duration in Weeks)

	18 year old Males			18 year Females		
Before-After Treatment Effect	-33.50** (6.00)			-30.79** (6.89)		
Decomposition	Overall Decomposition	Duration Effect	Incidence Effect	Overall Decomposition	Duration Effect	Incidence Effect
Training	-6.34	-10.19	3.85	-3.07	-3.64	0.58
Work	-14.80	-10.15	-4.65	-1.47	-16.65	15.18
Education	-2.84	-1.94	-0.90	-5.24	-0.98	-4.25
Other	-6.96	-8.07	1.11	-7.09	-7.81	0.72
Inactive	-2.57	-1.84	-0.73	13.98	0.05	-14.02

Figure 1: Duration Decomposition Profiles
18 year old Males

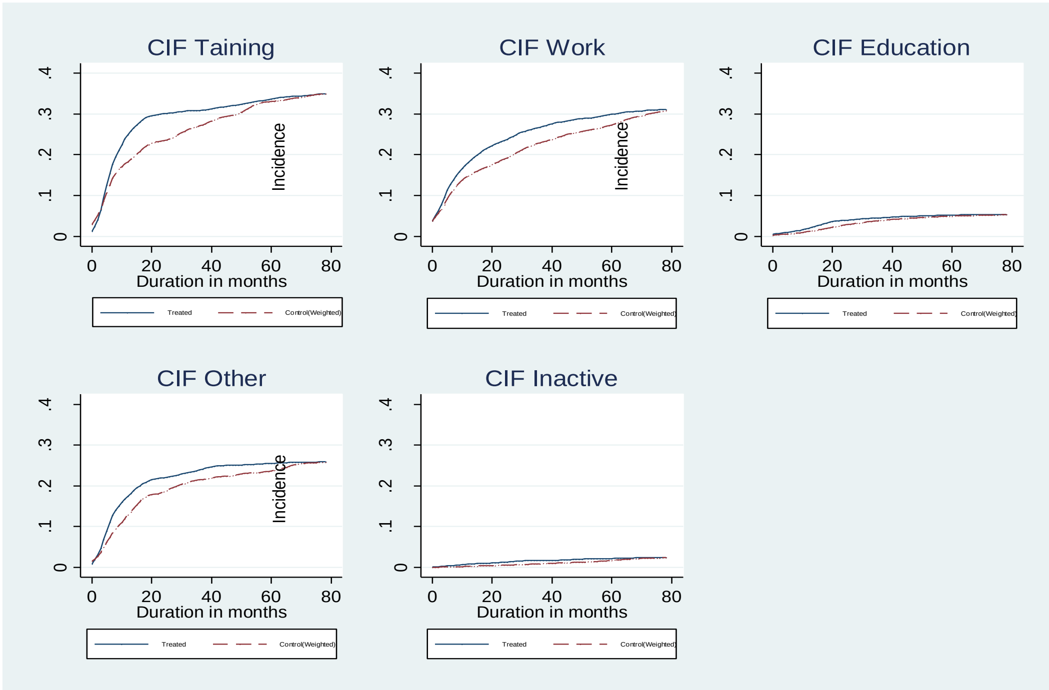


Figure 2: Duration Decomposition Profiles
18 year old Females

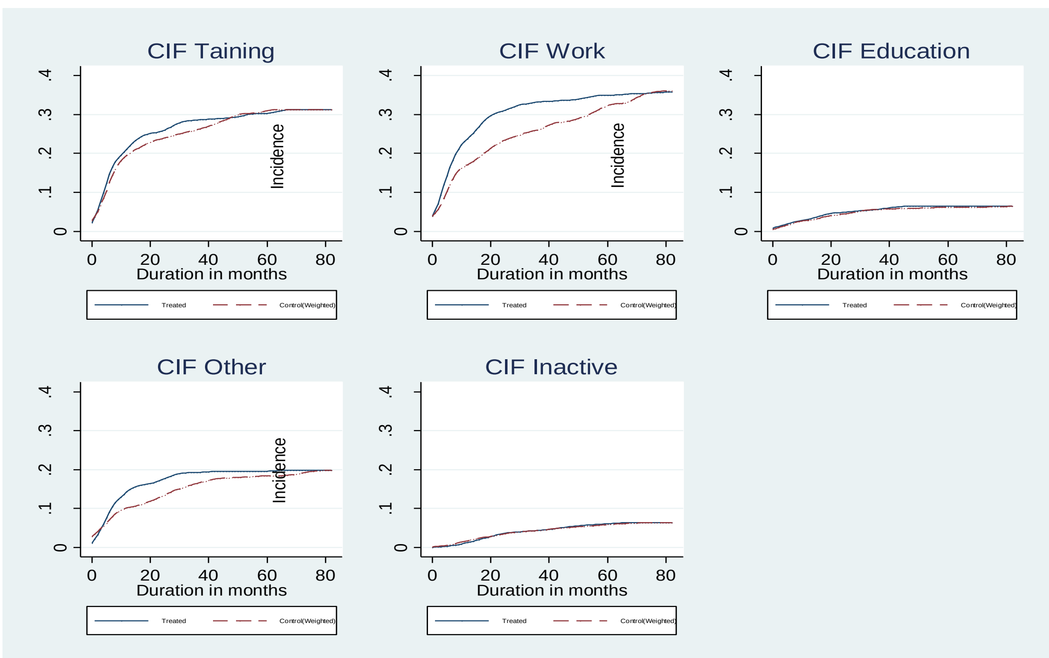
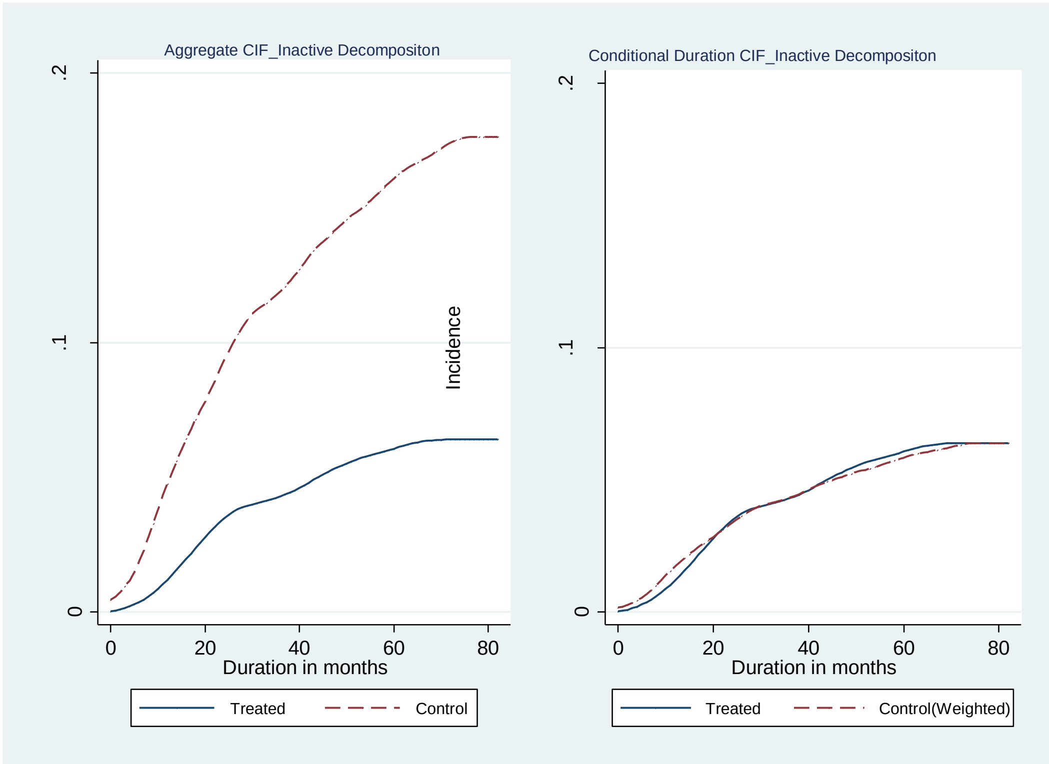


Figure 3: Duration Decomposition Profiles
18 year old Females



Appendix 1:

Theorem: Let Y be a random variable representing the duration of unemployment for group with upper bound T_M then

$$E(Y_T|K_T = k) = \left[T_M - \int_0^{T_M}\left[\left[\frac{(CIF_{kT}(y))}{f_{kT}}\right]dy\right]\right]$$

Proof:

$$E(Y_i|K_i = k) = \int_0^{T_M} y.f_i(y|K_i = k)\ \ dy$$

$$= \frac{1}{f_{kT}}\int_0^{T_M} y.f_{kT}.f_T(y|K_T = k)\ \ dy\ = \frac{1}{f_{kT}}\int_0^{T_M} y\ \ f_T(y,k)\ \ dy$$

$$=\frac{1}{f_{kT}}\int_0^{T_M} y\ \ \frac{dCIF_{kT}(y)}{dy}dy\ =\frac{1}{f_{kT}}\int_0^{T_M} Pr_T(Y > y, D = k)\ \ dy$$

$$=\frac{1}{f_{kT}}\int_0^{T_M}(1 - Pr_T(Y \leq y, D = k) - (1 - Pr_T(D = k))\ \ dy$$

$$= \frac{1}{f_{kT}}\int_0^{T_M}\big((Pr_T(D = k) - Pr_T(Y \leq y, D = k))\big)\ \ dy$$

$$\frac{1}{f_{kT}}\left\{T_M f_{kT} - \int_0^{T_M}\big[\big(CIF_{kT}(y)\big)\big]dy\right\} = \left\{T_M - \int_0^{T_M}\left[\frac{(CIF_{kT}(y))}{f_{kT}}\right]dy\right\}$$

Appendix 2:Dealing with Censored Observations

Let Y be a random variable representing the duration of unemployment for group with undefined upper bound and consider an arbitrary cut duration τ. Andersen (2013) showed that the difference in the τ-restricted mean lifetimes can be written as

$$e_T(0,\tau) - e_C(0,\tau) = \sum_k \left[\left\{ \int_0^\tau \{CIF_{kC}(y) - CIF_{kT}(y)\}\, dy \right\} \right]$$

To derive the extended decomposition in this instance define $\theta_k = \frac{Pr_T(Y \le \tau, D=k)}{Pr_C(Y \le \tau, D=k)} = \frac{CIF_{kT}(\tau)}{CIF_{kC}(\tau)}$ and rewrite

$$e_T(0,\tau) - e_C(0,\tau) = \sum_k \left[\langle \underbrace{\left\{ \left\{ \int_0^\tau \theta_k [CIF_{kC}(y)] dy - \int_0^\tau [CIF_{kT}(y)] dy \right\} \right\}}_{Duration\ \ Effect} \rangle + \langle \underbrace{\{1-\theta_k\} \left[\int_0^\tau [CIF_{kC}(y)] dy \right]}_{Incidence\ \ Effect} \rangle \right]$$

$$= \sum_k \left[\left[\left\{ \left\{ \underbrace{CIF_{kT}(\tau) \left\{ \left[\tau - \int_0^\tau \left[\frac{(CIF_{kT}(y))}{CIF_{kT}(\tau)} \right] dy \right] - \left[\tau - \int_0^\tau \left[\frac{(CIF_{kC}(y))}{CIF_{kT}(\tau)} \right] dy \right] \right\}}_{duration\ \ effect} \right\} \right\} + \underbrace{\{CIF_{kT}(\tau) - CIF_{kC}(\tau)\} \left[\tau - \int_0^\tau \left[\frac{(CIF_{kC}(y))}{CIF_{kT}(\tau)} \right] dy \right]}_{incidence\ \ effect} \right] \right] + \underbrace{R_\tau}_{Residual} \quad \text{(A1)}$$

where $R_\tau = \tau\{S_T(\tau) - S_C(\tau)\}$ is a residual term capturing differences in survival rates at time τ. It is straightforward to show that $\lim_{\tau\to\infty} R_\tau = 0$ provided $\lim_{\tau\to\infty} f_T(\tau) = \lim_{\tau\to\infty} f_C(\tau)$, so that the density of durations do not differ in the extreme tails.

Following the same approach to that used in Appendix 1, we can show that

$$E(Y_T|K_T = k, Y_T \leq \tau) = \left[\tau - \int_0^\tau \left[\left[\frac{(CIF_{kT}(y))}{CIF_{kT}(\tau)}\right] dy\right]\right].$$

Thus we can interpret the first component in the extended decomposition (A1) as the duration effect up to time τ and the second component as the contribution of differences in incidences as of time τ on differences in restricted means, with an additional residual effect that, under reasonable conditions, goes to zero as τ becomes large.

To proceed in the presence of censoring, simply recognise that the key components of this decomposition are $\int_0^\tau [CIF_k(y)]dy$, $CIF_k(\tau)$ and $S(\tau)$ and furthermore that unbiased estimators exist for these terms even in the presence of independent right censoring (see Andersen 2013). Implementing the decomposition simply requires replacing the unknown $\int_0^\tau [CIF_k(y)]dy$, $CIF_k(\tau)$ and $S_i(\tau)$ with their unbiased estimators.

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