

DREAM

Danish Research Institute for  
Economic Analysis and Modelling



# Forecasting the Impact of Pension Age Reform on Job Destruction Rates by Age in Denmark

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Model documentation

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[www.dreamgruppen.dk](http://www.dreamgruppen.dk)



# Preface

I use register data from Statistics Denmark to compute job destruction rates by age in Denmark between 2011 and 2018. The job destruction rate increases discretely at pension age and pension reform gradually delays the age at which this discrete increase takes place. The period 2013 to 2018 reflects the first impact of pension reform which is visible at age 60 which is the age of early retirement. The impact of pension reform at age 65 is not yet visible but I can use the observed impact of age changes on early retirement and the planned changes in pension age to generate future life cycle profiles for the job destruction rate that incorporate the entire pension reform. These can then be used as inputs in models where the job destruction rate is exogenous.

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# Introduction

I use register data from Statistics Denmark to compute job destruction rates by age in Denmark between 2011 and 2018. The job destruction rate increases discretely at pension age and pension reform gradually delays the age at which this discrete increase takes place. There are two turning points in retirement. The first occurs currently around age 60 and is the point of early retirement (Efterløn program). The second occurs around age 65 and is the standard retirement age. The first observable impact of changes in full retirement age occurs during the 2018 to 2019 employment transitions, and the complete data for this period is not yet available. However, we can extrapolate its effect from the observable effect of the early retirement reform.

Figure 1 shows the planned evolution of pension age by year of birth. Early retirement age is planned to rise from age 60 to 73.5 and full pension age is planned to rise from age 65 to 76.5, with the initial cohorts (those born in 1953 and shortly after) shouldering a higher proportion of the adjustment. As we will see from the job destruction data, the impact of early retirement reform on the first cohorts, born between 1953 and 1957, is already visible, and the impact of pension reform on the first cohort (born in 1953) will be visible as soon as the complete data for 2019 is available.<sup>1</sup>

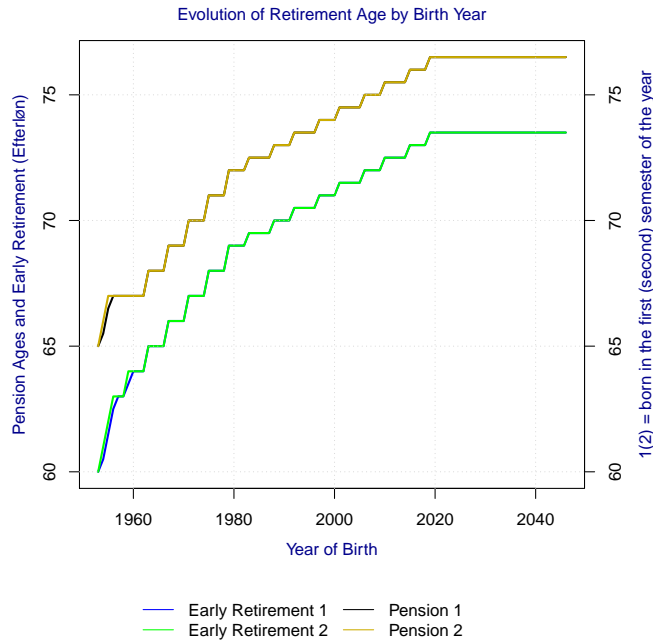


Figure 1: Planned Changes in Pension Age

1. <https://dreamgruppen.dk/aktuelle-temaer/arbejdsmarked/tilbagetraekningsreformer-og-folkepensionsalder/>

## Data

The register data contains the personal number, date of birth, gender, living address, and other personal information on individuals measured in the last quarter of each year. To this we match employment status information which contains monthly data on employment, wages, hours worked, total compensation, characteristics of the firm (firm and plant identifier, location, sector, type of job), etc. The data has information on whether a person is working, and conditional on working, how many hours he or she works and gets paid, how many different jobs they have, and if they work in the same firm in different periods. The data is restricted to wage earners and therefore self employed individuals are excluded. I also limit the focus to annual changes, thereby selecting data only from the month of November in every year. November is chosen as it is a month with closer to “normal” economic activity. Employment information in the month of November in year  $t$  is matched to personal information on each individual.

Crucial to obtaining job destruction and job finding measures from the data is the definition of what it means to be employed. Employment is defined as working more than one hour **and** earning any positive amount, and non-employment as working less than one hour **or** earning a zero amount. In the data we observe also that the same individual can receive multiple wage payments in a given month, so that a number of individuals can be counted more than once as they have more than one “job”. Non employment means zero jobs so in this variable individuals are counted only once. I eliminate this feature by selecting only the “job” with the largest paycheck in the period for each individual.

Apart from measuring the transitions in and out of employment, I am interested in measuring job changes. I use the firm identifier as conditioning variable in order to obtain employment to employment transitions. This variable is labeled AJO-CVR-NR-FRA-PROD-JOB and is the CVR number used to identify a company as a legal entity.

## Overview of the data

Table 1 shows data on population and employment for individuals aged 26 to 55.<sup>2</sup> Around three quarters of the population of these ages are employed, and 77.8% of men and 74.5% of women are employed in November 2018. Figure 2 shows the age profile of employment rates around retirement. The early retirement law changes are clearly visible postponing the decline in the employment rate. Also interesting is the absence of a sudden drop in employment at age 65, the natural process of leaving the labor force being the dominant effect. As the gap between the early retirement and full retirement ages is planned to narrow from 5 to 3 years this absence of a kink at full retirement may disappear, but as of yet we have no way of knowing if that will happen.

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2. This age interval is useful for looking at effects across time so we make use of it here also.

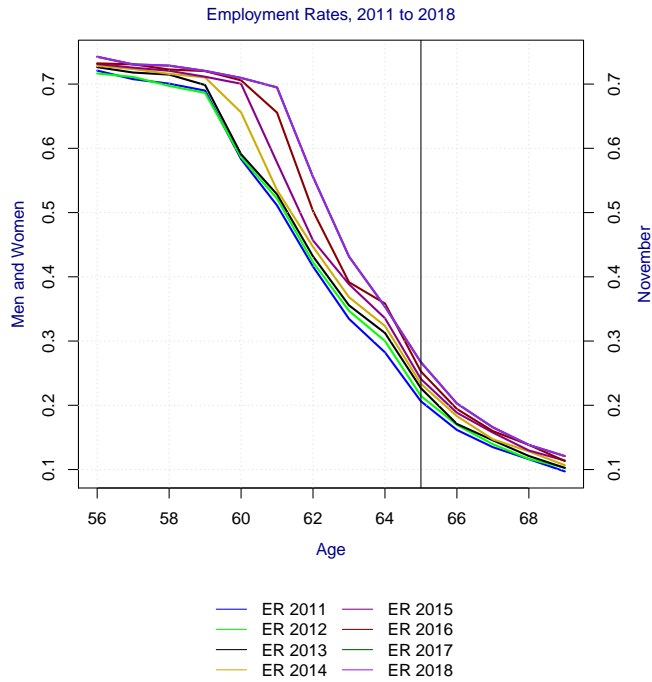


Figure 2: Early Retirement and Employment Rate

Table 2 shows data on unemployment and on jobs found out of unemployment for the same age interval. Unemployment is calculated as the difference between population and employment so it is best described as non-employment, and jobs found counts the number of individuals who are not employed in November of the first year and are employed in November of the following year. Around 19% of unemployed men and 20% unemployed women aged 26 to 55 find jobs, and from 2017 to 2018 the job finding rates are respectively 19.9% and 21.6%.

Table 3 shows data on employment and on jobs lost (transitions from employment at time  $t$  to non employment at  $t+1$ ) for individuals aged 26 to 55. Around 6% of employed men and 7% employed women aged 26 to 55 lose jobs, and from 2017 to 2018 the job loss rates are respectively 6.13% and 6.98%.

Table 4 shows employment to employment transitions. The first measure is unconditional and measures the number of individuals that have a job in the one period (November of the year described in the first row) and also have a job one year later. Any job. The second measure is conditional and is the number of individuals that have a job in both periods and that job has the same CVR number. These are people that have **not** changed jobs. The difference between the unconditional and conditional measures of employment to employment transitions provides the measure of job to job transitions (people staying employed but changing jobs). The crucial information contained in this measure is that it is much bigger in size than the number of jobs found out of unemployment. Most jobs found are found by people who already have jobs. For firms, the bulk of replacement activity occurs due to workers leaving for other jobs rather than

due to workers either retiring or becoming unemployed.

## Calculating job destruction and job finding rates

Job destruction is a transition from employment to non-employment. Employment to employment transitions are further detailed on the event of working for the same firm in different years. The difference between the unconstrained and constrained versions of employment to employment transitions produces a measure of job changes or job to job transitions. Job destruction rates can be computed either including or excluding job to job transitions, with significant implications for the level of job destruction and finding rates. Table 5 shows numbers for 40 year old individuals in 2017 and the numbers for 40 year old men are used in the immediate illustration.

We define the unconditional job finding rate as the ratio of transitions from non-employment to employment over the number of non employed,

$$x_t = \frac{U_t \rightarrow E_{t+1}}{U_t} = \frac{1323}{7239} = 0.183$$

This job finding rate is 18.3% for a 40 year old man unemployed in November 2017. We define also the unconditional job destruction rate as employment into unemployment transitions (employment minus job survival) over employment

$$\delta_t = \frac{E_t \rightarrow U_{t+1}}{E_t} = \frac{28156 - 26695}{28156} = \frac{1461}{28156} = 0.0519$$

and this destruction rate is 5.2% for a 40 year old man employed in November 2017.

Alternatively we define the total jobs found as the sum of non-employment to employment transitions plus job to job transitions (employment in job i into employment in job j). In this example we use the CVR number for job to job transitions (J2JCV):

$$JF_t = U_t \rightarrow E_{t+1} + E_t^i \rightarrow E_{t+1}^j = 1323 + 4413 = 5736$$

and define similarly total jobs destroyed as the sum of employment into unemployment transitions plus the same job to job transitions:

$$JD_t = E_t \rightarrow U_{t+1} + E_t^i \rightarrow E_{t+1}^j = 1461 + 4413 = 5874$$

and the job destruction rate is then given by

$$\hat{\delta}_t = \frac{JD_t}{E_t} = \frac{5874}{28156} = 0.209$$

The job destruction rate measured this way is 20.9% for a 40 year old man. For younger workers job destruction rates are higher. The job finding rate is then given by

$$\hat{x}_t = \frac{JF_t}{U_t + JD_t} = \frac{5736}{7239 + 5874} = 0.437$$

For the years 2017/2018 this global job finding rate measured above is very high, at 43.7% for a 40 year old man, because job to job transitions have a rate of 1 and account for a large part of jobs found. Job finding rates also fall with age.

## The life cycle

Figure 3 shows that job to job transitions decline steadily in importance as agents get older, with the steepest decline occurring early on between ages 20 and 30. Job changes occur mostly early in life. Figure 4 shows unconditional job finding and job destruction rates. The job finding rate out of unemployment (out of non employment),  $x_t$  is highest at the youngest ages and drops steadily over the life cycle, with a sudden steep drop around age 60 as individuals enter early retirement age. The job destruction rate  $\delta_t$  is the transition from employment into non employment and excludes job to job transitions. It is a U-shaped curve, highest at young and old ages and flat at around 5% between ages 40 and 60.

The smaller age windows in figures 3 and 4 highlight the impact of changes in the retirement law. In the case of finding and destruction rates this effect is clearly separable from any business cycle effect since we see a shift in the age at which the series has a kink and that kink identifies the early retirement effect. It is also very large. We see at the early retirement kink a jump in destruction rates from around 5 to around 15% and later at the pension age (65) a further jump to almost 30%. In the pension age we do not yet see the effect of the law but we can see the size of the jump at retirement. We can infer the effect of the law on the movement of the pension age kink and jump from its effect on the early retirement pattern.

There is one significant difference between the finding and destruction rates with respect to retirement. The destruction rate jumps up twice, first at the early retirement age and then at the pension age, but the finding rate jumps down only once, at the early retirement age. At and around age 65 there is no significant downward jump in the finding rate.

In the case of the job to job transition rate the different effects of the business cycle and the change in retirement law are not immediately distinguishable since the series does not have a marked kink. Any effect of the law on this variable will be picked by forecasting the destruction rate that includes job to job transitions.<sup>3</sup>

In what follows I focus on the destruction rate and not on the finding rate. The reason is that in many models the finding rate is endogenous while the destruction rate is an input into the model.

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3. At age 30 the job to job transition rate ranges from 0.169 to 0.199, at age 55 ranges from 0.076 to 0.100, while at age 60 it ranges from 0.053 to 0.072 and at age 62 from 0.053 to 0.061. The lower values occur in 2011-2012 and the higher in 2016 to 2018. At age 65 these rates cluster around 0.06 for the period, while there is still around 1/5 of the 65 year old population working (around eight thousand people). The effect of the law changes on job to job transition rates is likely to be one order of magnitude smaller than the effect on the destruction rate.



## Modelling the impact of changes in the retirement age

In order to forecast the impact of changes in the retirement age on the destruction rate I need to model it first. I do this in using a matrix with retirement age in columns and current date in rows. Each element  $[i,j]$  of this matrix identifies a cohort which is aged  $a(j)$  in year  $(i)$ . An increase in one year in the retirement age implies a given cohort retires one year later and one year older and therefore moves one row down and one column to the right. This is straightforward. Variations on this pattern require a small amount of additional attention.

When the half of the cohort born in the first semester retires half a year later than the previous cohort (for the cohort born in 1956 early retirement starts at age 62.5), and the half of the cohort born in the second semester retires one year later (at 63) the destruction rate jumps by one half of its full magnitude in the originally scheduled calendar year (62 years later, with the respective index  $[i,j]$ ). One year after that as that cohort moves down one row and one column to the right the full impact of the change is realized just as if they had all fully retired in the originally planned year. The jump at age 62 of that year is one half of the full jump. If there is a sequence of cohorts that have the same half year delay then for the column  $a(j) = 62$  we will see a sequence of rows where the destruction rate jumps half the full amount. There actually is not such a sequence of planned changes in the data. But there is another one with the same effect on the measured destruction rate.

If an entire cohort retires half a year later we see that same effect because the half of the cohort born in the second semester will retire only in the following calendar year when they are one year older. Again for a sequence of cohorts that have the same half year delay then for the respective column ( $a(j) = 70$  and  $71$ ) we will see a sequence of rows where the destruction rate jumps half the full amount.

Apart from allocating the correct time/age and magnitude of the discrete changes in the destruction rate, I allocate the last pre-jump destruction value for the entire extension of the working life, and to the right of full retirement, the last data-known sequence of destruction rates.<sup>4</sup> Figure 5 shows the result of the forecast procedure for the unconditional job destruction rate  $\delta$  and figure 6 shows the forecast for the full job destruction rate which includes job to job transitions.

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4. This is a first implementation of the forecast which focuses mainly on ensuring the job destruction rate jumps at the right time and by the right amount.

Table 1: Data: Population and Employment

	<i>Men</i>			<i>Women</i>		
	<i>N</i>	<i>E</i>	<i>E/N</i>	<i>N</i>	<i>E</i>	<i>E/N</i>
2012	1115795	838456	0.751	1101421	811911	0.737
2013	1115814	839968	0.753	1100737	810715	0.737
2014	1120024	847048	0.756	1101887	811790	0.737
2015	1129285	856378	0.758	1107508	814207	0.735
2016	1134854	868586	0.765	1111875	817877	0.736
2017	1138612	879291	0.772	1115492	825521	0.740
2018	1142328	888936	0.778	1118578	833590	0.745

N = Population, ages 26 to 55 (inclusive). E = Employment.

Table 2: Data: Jobs Found

Year	U	Men		U	Women	
		Jobs Found	JFR		Jobs Found	JFR
2012	277339	50647	0.183	289510	59653	0.206
2013	275846	51018	0.185	290022	60231	0.208
2014	272976	50896	0.186	290097	59498	0.205
2015	272907	52834	0.194	293301	60852	0.207
2016	266268	52162	0.196	293998	62673	0.213
2017	259321	51543	0.199	289971	62664	0.216
2018	253392	0		284988	0	

Ages 26 to 55 (inclusive). Of the 259321 men unemployed in November 2017 51543 are employed in November 2018, for a JFR of 19.9%.

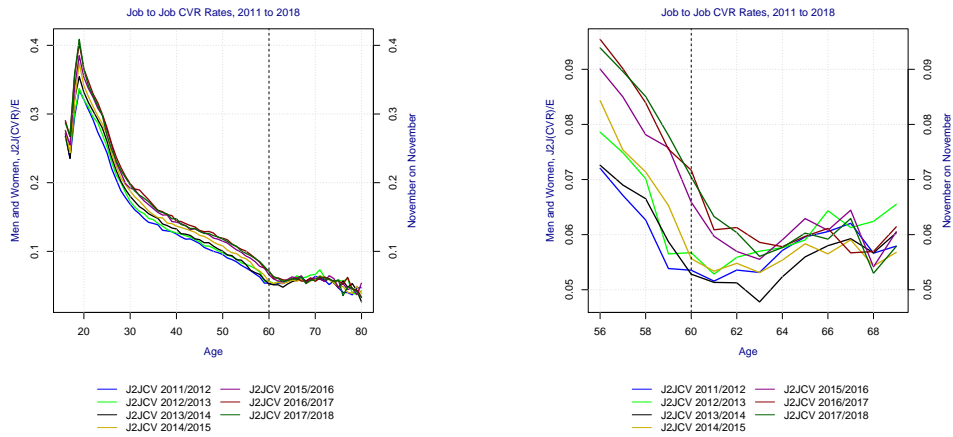


Figure 3: Job to Job Transition Rates

Table 3: Data: Jobs Lost

Year	Men			Women		
	E	Jobs Lost	JLR	E	Jobs Lost	JLR
2012	838456	55201	0.658	811911	59464	0.732
2013	839968	52013	0.619	810715	58904	0.727
2014	847048	51589	0.609	811790	58368	0.719
2015	856378	51092	0.597	814207	58523	0.719
2016	868586	52264	0.602	817877	56968	0.697
2017	879291	53875	0.613	825521	57599	0.698
2018	888936			833590		

Ages 26 to 55 (inclusive). Of the 879291 men employed in November 2017 53875 are not employed in November 2018, for a Job Loss Rate of 6.13%.

Table 4: Data: Employment to Employment Transitions

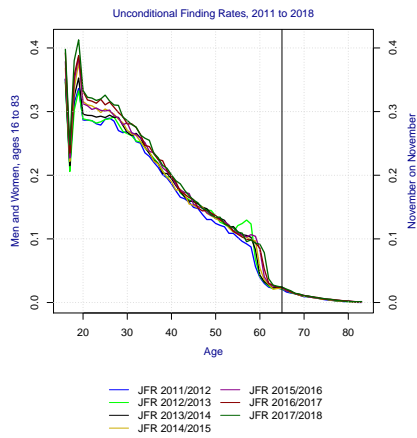
MEN	2012	2013	2014	2015	2016	2017
E→E	783255	787955	795459	805286	816322	825416
E→E <sub>cv</sub>	663490	666107	666522	669014	674451	684221
J→J <sub>cv</sub>	119765	121848	128937	136272	141871	141195
WOMEN	2012	2013	2014	2015	2016	2017
E→E	752447	751811	753422	755684	760909	767922
E→E <sub>cv</sub>	658438	653763	650748	647491	647541	654687
J→J <sub>cv</sub>	94009	98048	102674	108193	113368	113235

Individuals aged 26 to 55. E→E ≡ Working in both periods.  
E→E<sub>cv</sub> ≡ Working in both periods in the same CVRNR job.  
J→J<sub>cv</sub> = (E→E) - (E→E<sub>cv</sub>).

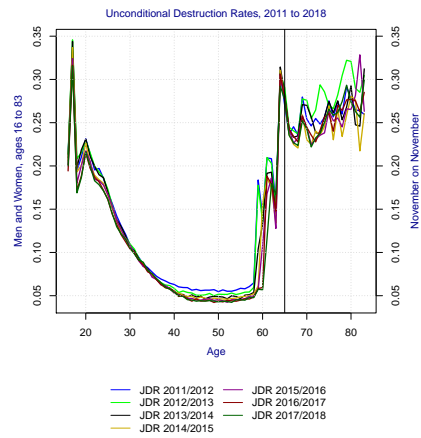
Table 5: Individuals Aged 40 in November 2017

	POP	EMP	UNP	SURV	J2JCV	JOBSF
<i>Men</i>	35395	28156	7239	26695	4413	1323
<i>Women</i>	35185	27044	7029	25511	3745	1762

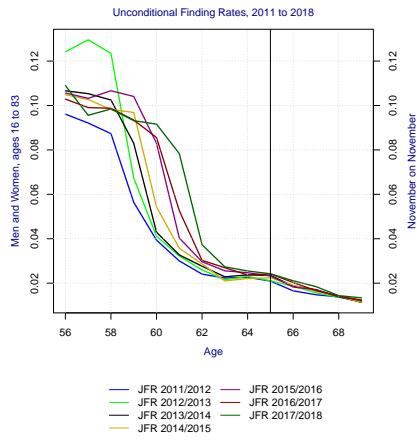
35395 men aged 40, 28156 employed, 7239 unemployed in November of 2017. Of the unemployed, 1323 are working in November of 2018. Of the 28156 employed in 2017, 26695 are working one year later.



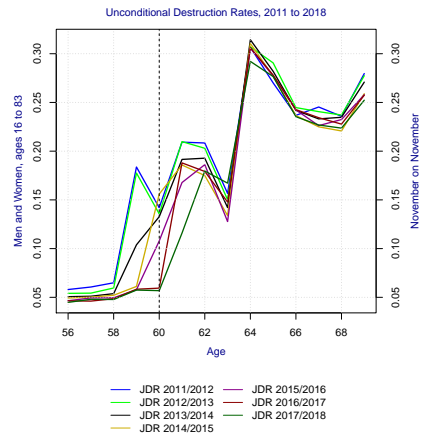
(a) Job Finding Rates



(b) Job Destruction Rates



(c) Job Finding Rates



(d) Job Destruction Rates

Figure 4: Unconditional Job Destruction and Job Finding Rates

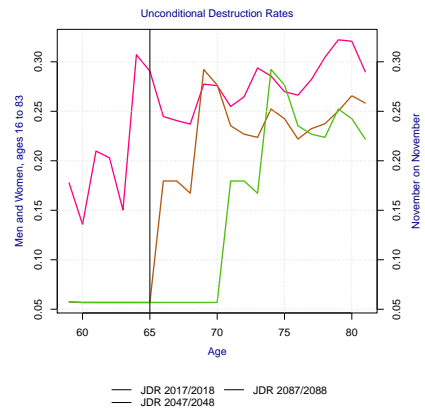
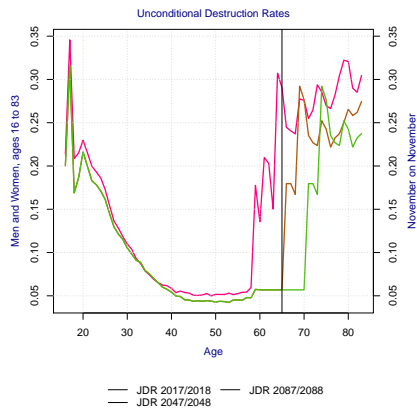


Figure 5: Job Destruction Rate Forecast

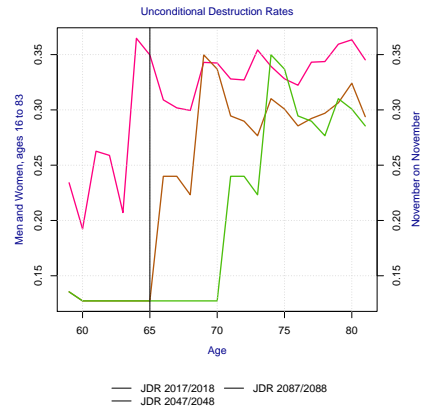
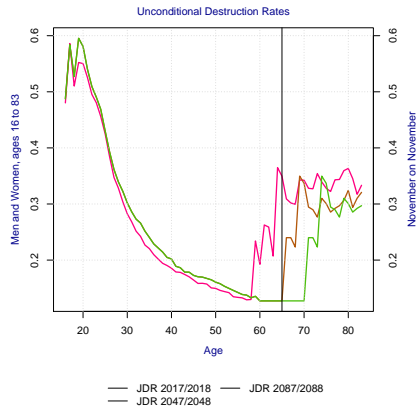


Figure 6: Full Job Destruction Rate Forecast