Strategic Behaviour in Work Absence: A Dynamic View

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Motivation

Work absenteeism is not uncommon and is costly for both workers and companies

- Approximately 3.3% of the U.S workforce do not report to work at any given day (Bureau of Labour Statistics data (2005)). Even higher in some developing countries (Duflo et al. (2012)).
- Absence replacement rates are usually less than 100%.
- Absenteeism costs account as high as 14.3% total payroll (Fister-Gale (2003)).

Worker's absence behaviours may be strategic:

- Define strategic: Preferences or constraints to future choices are altered by past experiences; State-dependent.
- Source of strategic behaviour: Company's absence regulation, absence scores $\rightarrow$ benefits.

Questions

- Do individuals respond to the absence scores? $\longrightarrow$ Estimate a 'deep' parameter.
- Do individuals respond differently towards different absence events? Short-term, long-term; ask for leaves, return to works
- How individuals make absence decisions? $\longrightarrow$ Economic Models

In the Literature

- History information (e.g, absence scores) is not considered in most empirical models. Fail to address the strategic absence behaviours: Delgado and Kniesner (1997), Barmby et al.(1991), Markussen et al.(2011) and Fevang et al.(2014).
- Use conventional tools: count data regressions, duration analysis, etc that hard to model state-dependent structure.

Motivation

In this paper

- Use self-exciting processes to model events (ask for leaves, return to work).
  - Self-exciting process is state-dependent
  - include past experiences
- Build econometric models that are depended on history: take absence scores into consideration.
- Main results:
  - Short-term absence events: respond to the absence scores
  - Long-term absence events: insensitive
- Inspired by the empirical results, construct a simple economic model.
- Compare new method with conventional count data regression and duration models.

Outline

1. Data, Preliminary Results and the Nature of Problem
2. The Econometric Models for Absenteeism
3. The Results
4. Economic Models
5. Discussion
6. Conclusion

Data

- A firm-level administrative data. The firm is UK based, produces homogeneous product.
- Has an experience rated work absence benefit scheme: lower absence scores correspond to a better financial benefit; renew every two years.
- Workers are categorised (with decreasing order) as class A, B and C based on previous two years' absence scores. The criteria scores are 21 and 41 respectively.
- All workers can receive UK statutory sick pay (SSP). To be eligible to receive SSP, workers should be absent from work for more than 3 consecutive days.
- Use data from calendar year 1987 to 1988. In total, 878 workers with 5718 absence records.
- Other literatures use this data: Barmby et al. (1991,1995), etc.

Data

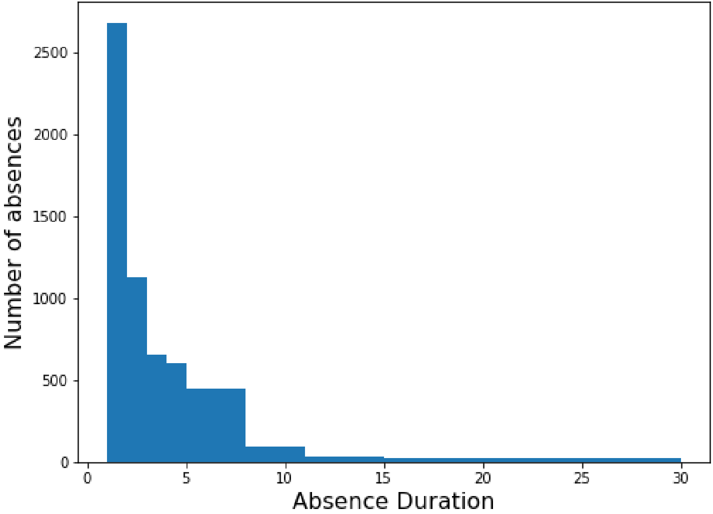


Figure: Most frequent absence durations

- Count Data Regressions
  1. Poisson
  2. Negative Binomial
  3. Hurdle Model (Zero part: binomial, count part: truncated negative binomial)
  4. Zero-inflation Model (Zero part: binomial, count part:negative binomial)
- Duration Models: Study the duration before the initial absence
  1. Standard: the hazard function is constant, no individual heterogeneity is concerned.
  2. Include individual heterogeneity, use Heckman and Singer's NPMLE.

	Dependent variable:			
	count88			
	Poisson	*negative binomial*	*hurdle count part*	*zero-inflated count part*
	(1)	(2)	(3)	(4)
age	−0.005	−0.006	−0.017	−0.005
	(0.011)	(0.016)	(0.012)	(0.012)
age2	0.007	0.008	0.015	0.0002
	(0.014)	(0.019)	(0.014)	(0.016)
sex	-0.249^{***}	-0.224^{***}	-0.230^{***}	-0.236^{***}
	(0.045)	(0.065)	(0.046)	(0.048)
full	0.104^{**}	0.115	0.094^{*}	0.115^{**}
	(0.049)	(0.074)	(0.050)	(0.052)
marriage	−0.066	−0.076	0.002	−0.011
	(0.052)	(0.075)	(0.056)	(0.059)
count87	0.131^{***}	0.156^{***}	0.086^{***}	0.101^{***}
	(0.005)	(0.008)	(0.006)	(0.006)
Constant	0.944^{***}	0.866^{***}	1.565^{***}	1.234^{***}
	(0.193)	(0.284)	(0.205)	(0.220)
Observations	874	874	874	874
Log Likelihood	-1,991.314	-1,878.365	-1,965.877	-1,940.922
θ		3.445^{***} (0.383)		
Akaike Inf. Crit.	3,996.627	3,770.731		
Note:	$age2 = age^2/100$. *p<0.1; **p<0.05; ***p<0.01			

For standard duration model, the hazard rate for individual i:

$$h_i = \exp(X_i' \boldsymbol{\beta})$$

$$H_i(T) = \int_0^T h_i(t)dt$$

X_i is a vector of covariates. The likelihood function:

$$L = \prod_{i=1}^{N} L_i = \prod_{i=1}^{N} \exp(-H_i(t))[h_i(t)]^{y_i}$$

y_i is the censoring indicator.
Include individual heterogeneity, the hazard rate:

$$h_i(t) = \exp(X_i' \boldsymbol{\beta} + \nu_i)$$

Use Heckman and Singer's NPMLE: Approximate the distribution of ν_i using discrete mass points.

Preliminary Results

Duration Model Results

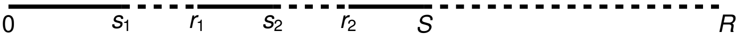
	Dependent variable:	
	duration	
	Standard	*Heckman & Singer*
age	-0.028***	-0.068***
	(0.006)	(0.026)
age2	0.047***	0.094***
	(0.010)	(0.032)
sex	-0.115	-0.133
	(0.093)	(0.113)
full	0.163	0.147
	(0.105)	(0.133)
marriage	0.076	0.119
	(0.099)	(0.127)
count87	0.254***	0.264***
	(0.010)	(0.013)
Observations	878	878
Log Likelihood	−248.668	-224.8397
χ^2	576.961*** (df = 5)	
Number of Mass Points		2
Note:		*p<0.1; **p<0.05; ***p<0.01

Nature of the Problem

Conventional methods can not model the strategic absence behaviours:

- Count Data Regressions aggregate information.
- Duration models have to maintain the i.i.d assumption among absences.
  - Multiple-spell models that allow lagged duration dependence
  - Estimate the joint duration likelihood function: must be a panel data setting.

We need to model the **State Dependent Structure** among absences.



s, S are starting dates and r, R are ending dates for short and long-term absences.

- State Dependence means past experiences have effects on future ones.
- Larger absence scores should discourage further absence behaviours.

Following Heckman (1981), construct a weekly panel data to test the state dependent structure. For each individual i, write the regression:

$$d(i,t) = \nu_i + \delta \sum_{t'<t} d(i,t^{'}) + U(i,t), t+1, \cdots, T$$

$d(i,t)$ is dichotomous choice, $\mathbb{E}(d(i,t)=1) = \Pr(\text{ask for a leave})$. ν_i is individual specific term, $U(i,t)$ satisfy usual fixed effect model assumptions.

$\hat{\delta} = -0.033316$ with a standard deviation of 0.00033: favours the existence of state-dependence in incidence data.

Outline

Intro to the Self-Exciting Process

The self-exciting process is a special counting process.

Counting process:

$$N(t) = \sum_i \mathbb{I}(t_i \leq t)$$

Doob-Meyer Decomposition:

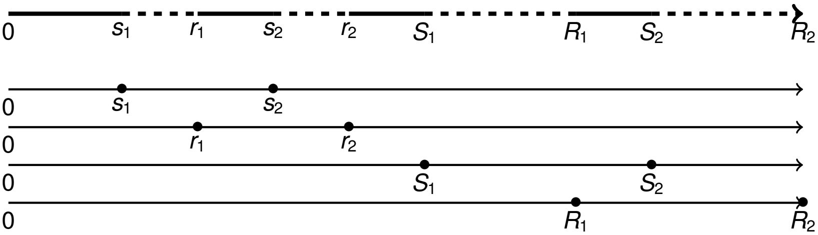
$$N(dt) = \Lambda(dt) + M(dt)$$

$\Lambda(t)$: predictable compensator, $M(t)$: local martingale.

The compensator may be conditioned on a filtration $\mathcal{F}(t)$. If $\mathcal{F}(t)$ includes $\sigma(N(s) : s \leq t)$, we call the associated counting process a **self-exciting process**. The self-exciting process is by design **state dependent**.

Study $N(t)$ via $\Lambda(t)$ or the intensity $\lambda(t) = \Lambda(dt)/dt$

- 'decompose' an absence into two events:
  - Incidence event: ask for a leave
  - Recovery event: return to work
- distinguish short and long-term absence:
  - use the duration of absences as criteria
  - the cut-off is 3 days: based on the UK's SSP regulation.
- have four counting processes.



Define 3 states that one individual can occupy:

- attendance: $k = 1$
- short-term absence: $k = 2$
- long-term absence: $k = 3$

$\lambda_{1k}(t)$: Short (Long) term incidence intensity, $k = 2, 3$;
$\lambda_{k1}(t)$: Short (Long) term recovery intensity, $k = 2, 3$;

The period between previous return date and the start date of next absence is called **attendance period**; the period between the start date and return date of same absence is called the **absence period**.

Let t denotes the starting dates and τ denotes the return dates. The duration of i^{th} absence is then $d_i = \tau_i - t_i$.

If individual *i* has no previous absence records, instead of intensity, we will study her hazard rate for the duration until first absence:

$$h_i = \exp(\nu_i) exp(\mathbf{X}_i' \gamma_{1k})$$

where ν_i is individual's random effect, $\mathbf{X}_i$ is a vector of covariates.

Two kinds of individuals fit into this situation:

- Never have absence before and not have absence in the study period (1987-1988): Censoring
- Never have absence before but have absence records in the study period.

Procedures:

- Construct a sub-dataset, using only initial absences
- Study the duration before the initial absence
- The hazard rate has the same interpretation as the intensity for the first event.
- Use Heckman and Singer's NPMLE to approximate the distribution of random effect term.

The overall incidence intensity for individual i, who has previous absence records would be:

$$\lambda_{i,1k}(t) = \begin{cases} \lambda_{1,k}(\mathbf{X}_i)\lambda_{2,k}(t)\Big(\lambda_{3,k}(t) + \lambda_{4,k}(t)\Big), t \in \text{attendance period} \\ 0, t \in \text{absence period} \end{cases}$$

where

- $\lambda_{1,k}(\mathbf{X}_i) = exp(\mathbf{X}_i'\gamma_{1k})$; $k = 2, 3$ contains all the time-invariant covariates
- $\lambda_{2,k}(t) = exp(\beta_{1k} H_i(t))$; $k = 2, 3$ governs the response of one worker to her own cumulative absence time $H_i(t)$.
- $\lambda_{3,k}(t) = 1 + |\alpha_{1k}| exp(\alpha_{1k}(t - \tau_{N_i^1(t-)}))$; $k = 2, 3$ measures the time dependence since previous recovery date.
- $\lambda_{4,k}(t) = a_{1k}(1 + sin(b + c_{1k}t))$; $k = 2, 3$ measures the individual's response to Mondays and Fridays. We set $c = 327.6$ such that the distance between two peaks in the sine function is equal to $7/365$ years, or one week's time.

The intensity for recovery process (return to work) has three parts:

$$\lambda_{5,k}(\boldsymbol{X}_i) = exp(\boldsymbol{X}_i'\boldsymbol{\gamma}_{k1})$$

$$\lambda_{6,k}(\tau) = |\beta_{k1}| exp(\beta_{k1} H_i(\tau))$$

$$\lambda_7(\tau) = 1 + |\beta_{k2}| exp(\beta_{k2}(\tau - t_{N^1_{i,13}(\tau-)})); k = 2, 3$$

The overall intensity for recovery process :

$$\lambda_{i,k1}(\tau) = \begin{cases} \lambda_{5,k}(\boldsymbol{X}_i)(\lambda_{6,k}(\tau) + \lambda_7(\tau)), \tau \in \text{absence period} \\ 0, \tau \in \text{attendance period} \end{cases}$$

We try to use history information to approximate the unobserved heterogeneity:

- In incidence process, the primary unobserved heterogeneity is the individual's working attitude.
- It can be approximated by an individual's average attendance duration.
- In recovery process, the primary unobserved heterogeneity is the individual's recovery ability.
- It can be approximated by an individual's average recovery time.

The (moving) average attendance duration $\tilde{d}(t)$ is defined as:

$$\tilde{d}(t) = \frac{\sum_{i:r_i \leq t} s_i - r_{i-1}}{\#\{i : s_i \leq t\}}$$

We assume it has the following structure:

$$\log(\tilde{d}(t)) = I(t) + log(1 + H(t)) + \epsilon$$

with $\mathbb{E}(\epsilon) = 0$.
We approximate $I(t)$ by $\tilde{I}(t)$:

$$\tilde{I}(t) = \log(\tilde{d}(t)) - log(1 + H(t)) = I(t) + \epsilon$$

We modify the $\lambda_{1,k}$ as:

$$\lambda_{1,k} = exp(\mathbf{X}_i' \gamma_{1k}) exp(\gamma^{'} \tilde{I}(t))$$

the structural of the overall incidence intensity remains the same.

The Econometric Models

Heterogeneity (3/4)

Similarly, the (moving) average recovery time $\tilde{c}(t)$ is defined as:

$$\tilde{c}(t) = \frac{\sum_{i:r_i \leq t} r_i - s_i}{\#\{i : r_i \leq t\}}$$

and it has the following structure:

$$\log(\tilde{d}(t)) = R(t) - log(1 + H(t)) + \epsilon$$

with $\mathbb{E}(\epsilon) = 0$.
We approximate $R(t)$ by $\tilde{R}(t)$:

$$\tilde{R}(t) = \log(\tilde{c}(t)) - log(1 + H(t)) = R(t) + \epsilon$$

We modify $\lambda_{5,k}$ as:

$$\lambda_{5,k} = exp(\boldsymbol{X}_i'\gamma_{k1})exp(\gamma^{'}\tilde{R}(t))$$

Alternatively, instead of assuming individual heterogeneity, we may assume group heterogeneity and use finite mixture Poisson model to 'reveal' the group affiliation.

Intuition: hard-working individuals tend to (on average) have fewer absences.

Assume k groups, the numbers of absences $\mathbf{y} = (y_1, \cdots, y_N)^{'}$ follows:

$$p(\mathbf{y}|\Theta) = w_1 f_1(\mathbf{y}|\Theta_1) + w_2 f_2(\mathbf{y}|\Theta_2) + \cdots + w_k f_k(\mathbf{y}|\Theta_k)$$

Θ_k: vector of parameters for group k, w_k: weight and $f_k(\cdot|\Theta_k)$: Poisson density.

Calculate the posteriors and assign group affiliation:

$$\begin{aligned} p(I_i = k|y_i, \Theta_k) &= \frac{p(y_i|I_i = k, \Theta_k) * p(I_i = k)}{p(y_i|\Theta_k)} \\ &= \frac{p(y_i|I_i = k, \Theta_k) * w_k}{\sum_{k=1}^{K} p(y_i|I_i = k, \Theta_k) * w_k} \end{aligned}$$

How to Estimate the Models

One result of the Doob-Meyer Decomposition:

$$\mathbb{E}N(t) = \mathbb{E}\Lambda(t)$$

Kopperschmidt and Stute (2013) propose a minimum distance estimation method to overcome the mentioned difficulty.

$$\nu_n = arg \inf_{\nu \in \Theta} ||\bar{N}_K - \bar{\Lambda}_{\nu,K}||_{\bar{N}_K}$$

where $||f||_{\mu} = \left[\int f^2 d\mu \right]^{1/2}$, with μ being a measure.

$\bar{N}_K = \frac{1}{K} \sum_{i=1}^{K} N_i$, $\bar{\Lambda}_{\nu,K} = \frac{1}{K} \sum_{i=1}^{K} \Lambda_{\nu,i}$.are the averaged counting process and compensator respectively.

The estimator is found to be consistent and asymptotically normal as long as all the observations are i.i.d.

How to Estimate the Models

The usual way to estimate a self-exciting intensity is the maximum likelihood based technique:

- require the intensity be predictable with respect to its filtration.
- often fails in complicated economic models as the existence of external shocks.
- the intensity should be predictable with respect to the self-exciting filtration as well as shocks.

In our application:

- The four counting processes are external shocks to each other
- The switches between attendance period and absence period are external shocks.

Outline

No previous absence records: study the duration before initial absence. Those who have no absence records throughout the whole study period are treated as censoring. Usual censoring assumptions applied.

	short term,k=2	*short term,k=2*	*long term,k=3*	*long term,k=3*
	(1)	(2)	(3)	(4)
age	-0.0392^{***}	-0.0696^{*}	-0.0654^{***}	-0.1000^{*}
	(0.0138)	(0.0402)	(0.0195)	(0.0529)
age2	0.0464^{**}	0.0817^{*}	0.0841^{***}	0.1240^{**}
	(0.0203)	(0.0484)	(0.0280)	(0.0633)
male	0.0834	0.0356	0.3175	0.1184
	(0.2253)	(0.2302)	(0.3461)	(0.3416)
full time	0.0703	-0.0039	0.4345	0.3861
	(0.2402)	(0.2561)	(0.3563)	(0.3602)
married	0.0357	0.0873	0.0894	0.1391
	(0.2015)	(0.2128)	(0.2570)	(0.2679)
Log Likelihood	-257.0000	-256.6635	-174.5000	-174.2110
Number of Mass Points	1	2	1	2

Note: Absence duration less or equal to 3 days are categorized as short term, others are long term. $age2 = age^2/100$. *p$<$0.1; **p$<$0.05; ***p$<$0.01

Incidence intensity estimation results, both short and long-term absences:

	Approx. Heterogeneity		*Group Heterogeneity*	
	short term	*long term*	*short term*	*long term*
	(1)	*(2)*	*(3)*	*(4)*
β_{1k}	-0.05734195***	0.002551	-0.03207249***	-0.02183574
	(0.007313)	(0.0108902)	(0.0072219)	(0.0139920)
α_{1k}	-35.32423495**	-5.02947189	-36.90188525*	-4.92911781
	(17.09965)	(6.4427670)	(21.600208)	(7.2625815)
age	0.31746598***	-0.42761261***	0.24439097**	-0.37079208**
	(0.0639588)	(0.1598638)	(0.1135570)	(0.1448501)
age2	-1.17953689***	0.96998791***	-1.53408411**	0.86544108***
	(0.3328688)	(0.3161102)	(0.6521555)	(0.2636461)
male	-2.02277622	-0.34993766	-4.62557647	-0.39203022
	(1.512623)	(1.0142152)	(12.506801)	(1.0577588)
full time	1.2947023***	1.22844682	0.7890032***	1.33575203
	(0.438272)	(1.2074113)	(0.1905531)	(1.2328672)
married	-1.03290089***	1.33187185*	-1.50756787**	1.32788344*
	(0.350615)	(0.7269884)	(0.6975158)	(0.6999908)
Mon/Fri	2.01429447*	0.15542535	5.00469984*	0.1711705
	(1.142056)	(2.6100053)	(2.6209058)	(2.9969653)
b	2.57708555***	2.69547261	2.58967502***	2.71009241
	(0.547747)	(7.8254215)	(0.2458489)	(8.4098623)
Group 2	–	–	1.01837705**	–
	–	–	(0.4682334)	–
$I(t)$	-0.42075577***	0.03062177	–	–
	(0.095787)	(0.1093162)	–	–
Distance	0.128602	0.028854	0.146190	0.0295902

Note: Absence duration less or equal to 3 days are categorized as short term, others are long term. β_{1k} are the coefficients of the absence score, α_{1k} are the coefficients of time dependent structure. *p<0.1; **p<0.05; ***p<0.01

- Cumulative absence time suppresses further 'ask for leaves' in both short and long-term cases.
- When making 'ask for leaves' decisions, individual face incomplete information set: how serious is the accident may not be clear.
- The decision making process between short and long-term absences are quite different:
  - Especially at age, marriage status, time dependence, Monday/Friday
  - Short term absences are more likely to be 'voluntary': maximise the individual utility
  - Long term absences tend to be 'involuntary': triggered by external shocks like illness.

Recovery intensities estimation results.

	short term,k=2 *original* (1)	*short term,k=2* *holiday* (2)	*long term,k=3* *original* (3)	*long term,k=3* *holiday* (4)
β_{k1}	0.0001905^{***}	0.0008113^{***}	$1.4540654 * 10^{-5}$	$9.0460202 * 10^{-6}$
	$(7.4389542 * 10^{-5})$	(0.0002250)	(0.0003066)	(0.0002337)
β_{k2}	-0.2974196^{***}	-5.4340119^{***}	-2.6893905^{***}	-1.2034950^{***}
	(0.0401992)	(0.5001305)	(1.0069173)	(0.3709412)
$R(t)$	-0.0192418	-0.0247104	-0.4945683^{***}	-0.6644247^{**}
	(0.0321509)	(0.0283878)	(0.0943706)	(0.2661450)
age	0.3777196^{***}	0.1760568^{*}	0.1905671^{***}	0.1039532^{***}
	(0.1333167)	(0.0968915)	(0.0476012)	(0.0227340)
age2	-0.8573565^{***}	-0.3947298^{**}	-0.5215264^{***}	-0.1656411^{***}
	(0.2791424)	(0.1820732)	(0.1408734)	(0.0444712)
male	-0.5670663^{***}	-1.2714456^{**}	4.1771252^{***}	4.6870273^{***}
	(0.2009157)	(0.5571283)	(0.3325700)	(0.3821019)
full time	-2.2429315^{***}	-1.0772366^{***}	-0.2411186	-1.7283286^{*}
	(0.5311679)	(0.2800427)	(0.3252895)	(0.9810031)
married	3.6464467^{**}	4.0556782^{***}	-1.5417979^{***}	-2.1603153^{***}
	(1.5006498)	(1.2085741)	(0.2369997)	(0.2075685)
Distance	0.100605	0.094431	0.061892	0.044357

Note: Absence duration less or equal to 3 days are categorized as short term, others are long term. $age2 = age^2/100$. β_{k1} are the coefficients of cumulative absence time. β_{k2} are the coefficients of time dependent structure. c is the coefficient of averaged

The Results

Recovery Process (2/4)

- Scheduled absences: e.g., absence related to holidays, information set is complete when making the absence decision; when asking for leave, the duration of that absence has already been known.
- The estimation results are biased; delete absences during the Christmas season to reduce the bias.
- Only short term recoveries respond to the cumulative absence time
- Long term recoveries are independent to the cumulative absence time
- Average recovery time is significant, but can not be interpreted as causal; rather it approximates (unobserved) recovery ability.
- Better to use conventional duration model to analysis long term recoveries.

For each individual i, the hazard rate is:

$$h_i = exp(X_i\beta^{'} + \nu_i)$$
$$H_i(T) = \int_0^T h_i(t)dt$$

the likelihood contribution is:

$$L_i(\nu_i) = \prod_{j\in S_i} exp(-H_i(t_j))h_i(t_j)$$

S_i: the set of observed long term durations for individual i.

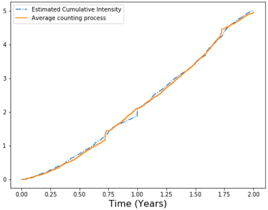
Use Heckman and Singer's NPMLE to estimate

Duration analysis for long term absences

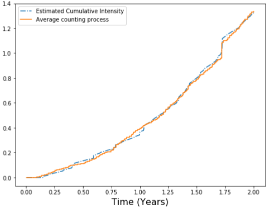
	long term,k=3
	holiday
age	0.07259135***
	(0.0128741)
age2	-0.12391056***
	(0.0237107)
male	0.04056263
	(0.0761176)
full time	-0.09775137
	(0.0969011)
married	-0.26665599**
	(0.0963911)
log-likelihood	3390.528
Number of Mass Points	2

Note: *age*2 $=$ *age*$^2/100$. *b* is the coefficient of duration dependence. *p$<$0.1; **p$<$0.05; ***p$<$0.01

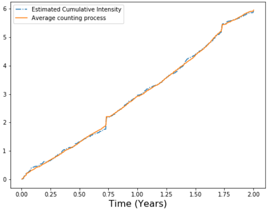
Overall our models fit the data well.



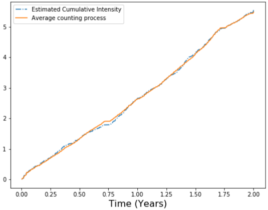
(a) Short term incidence



(b) Long term incidence



(c) Short term recovery (Original)



(d) Short term recovery (Bias Reduction)

Question: does individual's attitude towards the cumulative absence time changes as seniority grows?

Modify:

$$\lambda^*_{2,2}(t) = \exp(\theta(age)H(t))$$

where $\theta(age) = \beta_0 + \beta_1 age + \beta_2 age^2/100$

Other components and the structural of both incidence and recovery intensities remain unchanged.

	Incidence Intensity *short term* *k=2*
β_0	-0.34215516* (0.1904758)
β_1	0.03407675 (0.0280976)
β_2	-0.08642652 (0.0960550)
α_{1k}	-39.37455248** (18.741119)
b	2.61810899*** (0.3692254)
age	0.2953078*** (0.0991777)
age2	-1.1536771** (0.5079094)
male	-2.0585887 (1.7245835)
full time	1.31545004*** (0.5182786)
married	-1.02333993** (0.4207051)
Mon/Fri	2.35010473** (1.1141944)
$I(t)$	0.28212665*** (0.0913577)
Distance	0.107879

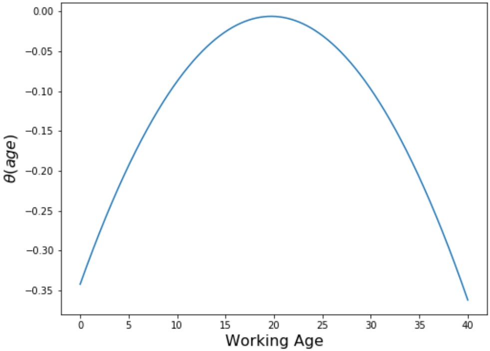
Note: Absence duration less or equal to 3 days are categorized as short term, others are long term. $age2 = age^2/100$. We delete absences during the Christmas seasons. *p<0.1; **p<0.05; ***p<0.01

Wald Test:

- Test 1: do individuals respond to the cumulative absence time
  - $H_0 : \beta_1 = \beta_1 = \beta_2 = 0$
  - $H_1 : \beta_1 \neq 0, \beta_1 \neq 0, \beta_2 \neq 0$
- Test 2: do individuals' attitudes about the cumulative absence time varies as working age changes
  - $H_0 : \beta_1 = \beta_2 = 0$
  - $H_1 : \beta_1 \neq 0, \beta_2 \neq 0$

Statistics for the Wald tests are 22334.637 and 355.045 respectively.

Figure: $\theta(age)$ in Short term incidence



- So far, we select the cut-off based on the UK's SSP Regulation: three days of absence
- Redefine the short and long-term absence by individual's response to the cumulative absence time:
  - short-term: individuals respond to the cumulative absence time.
  - long-term: no responses to the cumulative absence time.
- The coefficients of cumulative absence time satisfy:
  - the short term coefficient β_{12} and β_{21} are significant away from zero
  - the long term coefficient β_{13} and β_{31} are insignificant

	Incidence Intensities			*Recovery Intensities*	
	short term		*long term*	*short term*	*long term*
Cut-off	*Mon/Fri*	β_{12}	β_{13}	β_{21}	β_{31}
$c = 2$	1.59447952**	-0.1094399***	-0.05018605**	0.0006166***	0.00030766
	(0.5741051)	(0.0289985)	(0.0214045)	(0.0001899)	(0.0009172)
$c = 3$	2.01429447*	-0.05734195***	0.002551	0.0008113***	$9.046*10^{-6}$
	(1.142056)	(0.007313)	(0.0283703)	(0.0002250)	(0.0002337)
$c = 4$	1.08155452	-0.0466356***	0.00378901	0.0003203	$6.802*10^{-6}$
	(0.7767747)	(0.0119311)	(0.0110785)	(0.0002460)	(0.0002879)
$c = 5$	0.54790203	-0.05774703***	-0.00752412	0.0000130	$9.353*10^{-6}$
	(0.3641992)	(0.0121355)	(0.0484371)	(0.0004401)	(0.0004270)

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$

- The proper cut-off under new definition is still three days
- Importance of Social Security Regulation!

Outline

Ask for Leaves

- Accident, represented by a random variable $e \in [0, \infty)$
- The size of an accident is not revealed at the first place.
- Duration of an absence is determined by the accident: $a(e)$
- Individual Utility is determined by personal reputation, well-beings, and consumption

The decision to ask for a leave is governed by:

$$D = \mathbb{I}\{U(R(A + a(\mathbb{E}(e))), \omega^{'} - \mathbb{E}(e) + g(a(\mathbb{E}(e))), C_1) + \epsilon_1 > U(R(A), \omega^{'} - \mathbb{E}(e), C_2) + \epsilon$$

$$= \mathbb{I}\{U^1 + \epsilon_1 > U^0 + \epsilon_2\}$$

$R(\cdot)$: reputation, determined by the cumulative absence time A, in addition, $R^{'}(\cdot) < 0, R^{''}(\cdot) < 0$; ω: a stock of well-beings, $g(\cdot)$: well-being generating function with $g^{'}(\cdot) > 0$; C: consumption. ϵ:unobserved factors.

Utility function satisfies: $U_R, U_\omega, U_C > 0$, partial derivatives are positive.

Notice:

$$
\begin{aligned}
Pr(D=1) &= Pr(\epsilon_2 - \epsilon_1 < U^1 - U^0) \\
&= F_\epsilon(U^1 - U^0)
\end{aligned}
$$

where $\epsilon = \epsilon_2 - \epsilon_1$.

Since $F^{'}(\cdot) > 0, U_R > 0$ and $R^{'}(\cdot) < 0$. We have:

$$
\frac{\partial Pr(D=1)}{\partial A} < 0
$$

Return to Work:

- Strategic behaviours only exist in the short-term recovery processes
- A threshold of the size of an accident: e^* (with its corresponding absence duration $a(e^*)$)
- Within this threshold, individuals consider reputation; above this threshold, reputation is out of equation.

If $e \in [0, e^*]$ (short-term absences), the worker's problem is

$$\max_a U(R(A+a), \omega - e + g(a), C)$$

$$s.t$$

$$I + w(t^c - a) + R(A+a) - C = 0$$

I: non-labour income, w: wage, t^c contractual working time.

First Order Conditions:

$$U_R R^{'} + U_\omega g^{'} - U_C(w - R^{'}) = 0$$

$$(w - R^{'}) = \frac{U_R R^{'} + U_\omega g^{'}}{U_C} > 0$$

and

$$\frac{\partial a}{\partial A} < 0, \frac{\partial a}{\partial R} > 0$$

If $e \in [e^*, \infty)$ (long-term absences), for individual i in j^{th} long-term recovery period:

- Has a positive utility flow: $K_{ij} Z_1(t)\phi_1(X_i)$, K_{ij} is a positive random variable, may represent initial health status; $Z_1(\cdot), \phi_1(\cdot)$: functions of time and individual covariates respectively.
- If choose to return to work: receive an utility flow $Z_2(t)\phi_2(X_i)$.

Assume an exponential discount rate ρ, worker's problem:

$$\max_{t_{ij}} \int_0^{t_{ij}} K_{ij} Z_1(s)\phi_1(X_i)e^{-\rho s} ds + \int_{t_{ij}}^{\mathbb{E}(T)} Z_2(s)\phi_2(X_i)e^{-\rho s} ds$$

$\mathbb{E}(T)$: expecting beginning time of a next long-term absence.

This model is essentially a simplified version of Honor and De Paula (2010).

First Order Condition:

$$K_{ij} Z_1(t^*_{ij})\phi_1(X_i)e^{-\rho t^*_{ij}} - Z_2(t^*_{ij})\phi_2(X_i)e^{-\rho t^*_{ij}} = 0$$
$$K_{ij} - Z(t^*_{ij})\phi(X_i) = 0$$
$$t^*_{ij} = Z^{-1}(K_{ij}/\phi(X_i))$$

where $Z(\cdot)\phi(X_i) = Z_2(\cdot)\phi_2(X_i)/\big(Z_1(\cdot)\phi_1(X_i)\big)$.

Notice:

$$\ln Z(t^*_{ij}) = -\ln \phi(X_i) + \epsilon$$

where $\epsilon = \ln K_{ij}$.

- Assume $Z(t) = t$, $\phi(X_i) = e^{-X_i^T \beta}$ and $K_{ij} \sim \exp(1)$
- Is the accelerated failure time (AFT) model
- The corresponding hazard rate: $h_{t^*_{ij}}(t) = \exp(-X_i^T \beta)$

We can estimate this model:

	Dependent variable:
	duration
age	-0.26440^{***}
	(0.00685)
age2	0.44302^{***}
	(0.01569)
male	-0.58349^{***}
	(0.07593)
full time	-0.09395
	(0.08192)
married	0.14154^{*}
	(0.08066)
Observations	1,204
Log Likelihood	2,971.49500
χ^2	-362.47690 (df = 4)
Note:	*p<0.1; **p<0.05; ***p<0.01

Outline

- Poisson is the basic model of count data regression
  - require the equidispersion: the mean and variance should be equal
  - can not fit excess-zeros data
- Usual way to deal with the excess-zeros data: zeros and positives come from two data generating processes
  - Hurdle model
  - Zero-inflation model
- Simulation intensity function: $\lambda(t|\mathcal{F}_{t-}) = \mu + \sum_{i:t_i<t} e^{\alpha x_i} \left(1 + \frac{t-t_i}{c}\right)^{-p}$
- Generate data that
  - exhibits over-dispersion and
  - excess of zeros

- mean: 3.27
- variance: 108.54

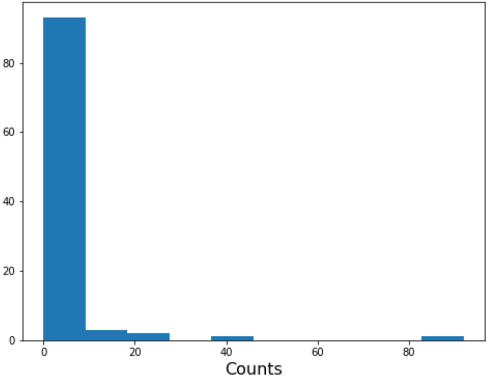
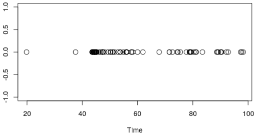


FIGURE: Result of Self-Exciting Process Simulation

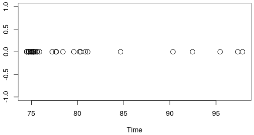
Compare to Duration Model (1/2)

- Duration model deals with the duration of a single event
- Self-exciting processes deals with recurrent events
- When describes a single event, the hazard rate and the intensity have the same interpretation
- Self-exciting may generate enough heterogeneity even without the unobserved heterogeneity.

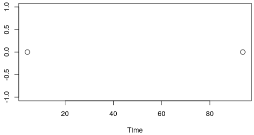
Using the same data generating process as before:



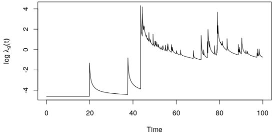
(a) Individual 1, Event Time



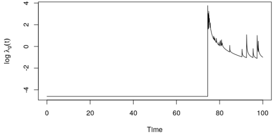
(b) Individual 2, Event Time



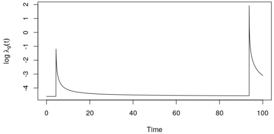
(c) Individual 3, Event Time



(d) Individual 1, log of intenstiy



(e) Individual 2, log of intenstiy



(f) Individual 3, log of intenstiy

Outline

Conclusion

In this paper, we

- provide substantial evidence on the existence of strategic absence behaviour
  - this is done by using the self-exciting process
  - study both ask for leaves and return to work decisions
  - distinguish short and long-term absences
- Only in the short-term events, individual cares about the cumulative absence time
  - can be used as one criteria to separate short and long-term absences
- build economic models to explain the empirical findings
- discuss self-exciting process as a complementary tool to conventional methods

Thank You !