A continuous-time Markov process for mobility in the labor market: the impact of breast cancer diagnosis in the case of French females*

Vanessa BASCETTO[1,2,3]; Jean-Paul MOATTI[1,2,3]; Alain PARAPONARIS[1,2,3]; Luis SAGAON TEYSSIER[1,2,3,4]

[1] INSERM, U912 (SE4S), Marseille, France
[2] Université Aix-Marseille, IRD, UMR-912, Marseille, France
[3] ORS PACA, Observatoire Régional de la Santé Provence Alpes Côte d'Azur Marseille France
[4] GREQAM, CNRS Research Unit 6579, Marseille

Abstract

This article investigates whether a cancer event might be transformed into a permanent loss in employment conditions. For this, we re-evaluate the impact of cancer on labor market conditions using *comparative* transition matrices between occupational states. We obtain a set of statistics based on estimations using continuous-time Markov transition processes, and we employ these to study and compare labor market dynamics in two populations: individuals diagnosed with cancer and their counterparts in the general population matched with propensity score. The consequences of cancer diagnosis were measured by a significant deviation in the transition matrix for cancer survivors as compared to a prior matrix standardized based on the general population. Data were stratified by social class, first to allow for a clear separation with regard to cancer-specific impacts, and second to take into account other stigmas in the labor market that are inherent to the subpopulations we examined. We also consider systematic differences in socioeconomic status and the ability to return to work.

Keywords Breast cancer survivors, mobility in the labor market, Markov modeling

* The authors thank the members of the Cancer Study Group (Groupe d'Etude ALD Cancer) : Guy-Robert Auleley (Caisse nationale du RSI, Paris), Pascal Auquier (Université de la Méditerranée, Marseille), Philippe Bataille (Université Lille 3, Lille), Nicole Bertin (CNAMTS, Paris), Frédéric Bousquet (HAS, Paris), Anne-Chantal Braud (Institut Paoli-Calmettes, Marseille), Chantal Cases (IRDES, Paris), Sandrine Cayrou (Toulouse),Claire Compagnon (Paris), Paul Dickes (Université Nancy 2 - GRAPCO - LABPSYLOR, Nancy), Pascale Grosclaude (Registre du cancer du Tarn, Albi), Anne-Gaëlle Le Corroller-Soriano (INSERM 912, Marseille), Laëtitia Malavolti (INSERM 912, Marseille), Catherine Mermilliod (DREES, Paris), Jean-Paul Moatti (Université de la Méditerranée & INSERM 912, Marseille), Nora Moumjid-Ferdjaoui (GRESAC - Université Lyon 1, Lyon), Marie-Claude Mouquet (DREES, Paris), Lucile Olier (DREES, Paris), Frédérique Rousseau (Institut Paoli-Calmettes, Marseille), Gérard Salem (InCa, Paris),Christine Scaramozzino (Ligue Nationale contre le Cancer, Paris), Florence Suzan (Institut de Veille Sanitaire, Saint-Maurice), Vincent Van Bockstael (CCMSA, Paris), Alain Weill (CNAMTS, Paris). The Cancer Study has been realized with the joining efforts of the Department for Research, Studies, Assessment and Statistics (DREES) of the French Health Ministry, the Inserm Research Unit 912 (*Economic & Social Sciences, Health Systems & Societies*), the three major sickness funds and their medical department (CNAMTS, CCMSA and Caisse Nationale du RSI) and the Ligue Nationale contre le Cancer. They also thank Sophie Eichenbaum-Voline (INSERM 912, Marseille) for research assistance.
Grant from the program *Workplace position and careers of cancer survivors* financed by the French National Cancer Institute (Institut National du Cancer, InCa) and the National Agency for Research (ANR) within the program *Vulnerabilities: the articulation of health and social* is greatly acknowledged.
Correspondence should be sent to: luis.sagaon_teyssier@etumel.univmed.fr (Luis SAGAON TEYSSIER)

Introduction

The importance of cancer in general public health, as well as in the day-to-day lives of many among us, is self-evident. During the last 20 years, breast is the most frequent localization of mortal cancers for females in France. At the same time, the mortality rate of cancer has declined of almost 1.5 percentage point between 1990 and 2002 (the mortality rate passed from 34.5% to 33%). Moreover, in the recent years, deaths occur relatively more in late-age categories. These features reflect the improvement of the diagnosis procedures, the prevention methods and a better care providing which extend the life expectancies of diagnosed females. Consequently, an increasing number of cancer survivors return to work after their treatment or while they are being treated. However, during and after these treatments, patients face physical and psychological after-effects that likely impact many aspects of their day-to-day lives, including their professional lives.

Previous studies have shown that a change of job or employer, a shift to part-time work, unemployment, and early retirement are common among cancer survivors (Short et al., 2005). Meanwhile, a return to work after treatment is associated with a better quality of life (Hoffman, 1999; Spelten et al., 2002; Bloom et al., 2004). In addition, the previous research points to a number of ways in which cancer may affect employment, including physical limitations (Chirikos et al., 2002; Bradley and Bednarek, 2002), emotional problems (Greaves-Otte et al., 1991), difficulties with concentration and memory (Schagen et al., 1999) and changing personal priorities (Maunsell et al., 1999; Hoffman, 2005). Negative interactions with co-workers (Greaves-Otte et al., 1991; Maunsell et al., 1999) and employers are also an ongoing concern. A recent paper (Short et al., 2005) concluded that "efforts to quantify employment problems associated with cancer survival have been hampered by small sample sizes, lack of longitudinal data, and an inability to account for differences by cancer site".

In this paper, we propose statistics based on estimations generated using continuous-time Markov transition processes. The method for estimating probabilities of transitions' matrices closely follows the work of Fougère and Kamionka (1992). Our analysis is also enriched by two matched databases: individuals diagnosed with cancer and a control group sampled from the general population. Propensity scores are used for matching. This method makes possible two new contributions to the literature:

- The capacity to account for the role of cancer diagnosis in explaining differences in returning to work among the non-employed. One of the main goals of the paper is that we take into account transitions not only from employment to non-employment, but also among various states.
- We use our estimations to simulate the probabilities of staying employed after the diagnosis, or leaving employment. At the same time the simulation of the job loss is made taken into account two possible exits towards non-employment or towards retirement. These simulations give an idea of the consequences that the breast cancer diagnosis has in the long-run.

The paper is organized as follows. Section 2, presents the data and the matching strategy used to link cancer survivors to their counterparts taken from a general survey on employment. The section 3, is devoted to the presentation of the continuous-time Markov model. The results about the impact of cancer upon mobility are presented in the section 4 by taking into account the role of the SES. Finally, we discuss our results in the section 5.

2. The data and the propensity score matching process: reduction of the sample bias between the cancer survivors and the general population

In this paper, we use two databases. The first database was collected by the French Health Ministry in late 2004 and includes information about the living conditions of adult patients diagnosed with cancer between September and October 2002. The second database is the employment survey (ES) conducted by the National Institute of Statistics and Economic Studies (INSEE by its initials in French). As commented above, this paper focuses on whether cancer survivors' trajectories in the labor market are impacted by illness. This kind of study requires the existence of a reference group. In other words, we are trying to isolate the differences between the transition patterns of two groups, namely individuals diagnosed with cancer (diagnosed group) and individuals without cancer (non-diagnosed group). Both groups include individuals aged from 18 to 57 years at the first interview who are both employed and non-employed. Additionally, we have removed all cancer survivors who are in a sick-leave period at the time of the interview (2004).

The existence of significant differences among the characteristics of the samples introduces a large sample bias that could compromise the inferences based on our estimations. In table 1, we observe contrasted differences concerning the selected socio-demographic characteristics. The cancer group is formed by females relatively more aged than the group issued from the general population. Important differences are observed in the professional status at the time of the first observation (time of diagnosis for the breast cancer survivors): for example, the proportion of females searching for a job (unemployed) is higher on the side of the general population (7,6%) than on the side of the cancer group (5,5%). Other differences concern the SES groups. There are relatively more breast cancer survivors belonging to the high SES[1] (80%) than females issued from the general population (62,5%). The mobility patterns between the different states of the labor market cannot be compared without treating the sample bias between the diagnosed and the non-diagnosed groups. For assessing the impact of the breast cancer diagnosis on the labor market trajectories it is necessary to reduce the differences between the two groups. That is, the cancer and the general population groups have to be balanced in that concerning the observed characteristics: comparing two groups with similar characteristics could offer more "realistic" information about the effect of being diagnosed of breast cancer on the mobility patterns into the labor market.

There are many methods for reducing the bias of these differences in order to reduce the differences between the diagnosed and non-diagnosed groups; for a review of matching methods, see Becker and Ichino (2002). One particularly refined method first creates a propensity score to represent the relationship between multiple characteristics and an outcome as a single score and then generates matching data on that single score.

To make comparable the diagnosed and non-diagnosed groups, we apply the *propensity score case-control* technique. Thus, we firstly estimate a probit of being in the cancer sample: in fact, we estimate the probability that an individual appears in the cancer-diagnosed group according to different socio-demographic characteristics. We estimated this probability (propensity score) on age, a dummy variable for female having at least 1 child aged less than 18 years, education level, the professional status (with the inactivity as reference group), the socioeconomic status, the size of the urban area. It is important to recall that the matching

1 The low SES category includes: farmers, artisans, factory workers, and drivers. The high SES category includes: top executives, intermediate professionals, and white-collar.

procedure is not the main methodology of this study and it is used only for preparing the data. Thus, the details on the *propensity score case-control* technique are showed in the appendix 1.

Table 2 shows the after-matching samples which constitute together a sample of 998 females. The importance of this technique can be illustrated by the professional status at the first observation (time of diagnosis for cancer survivors) and the professional status two years after. Only the proportions of the former are similar with around 85% of employed females in both cancer and general population groups. In addition the proportions of inactive and retired females are quite similar between the two samples. Although the similar proportions between groups give account of the effectiveness of the *propensity score case-control* technique for balancing the samples, in the figures of the appendix 2a-b we clearly observe that the sample bias was reduced: we show for example the Quantil-Quantil differences (Q-Q plot in appendix 2a) indicating that the empirical distribution created after the matching procedure is the same between the diagnosed and the non-diagnosed samples. In fact the Q-Q plots show that the most part of the points lie on the 45° diagonal. Similarly the figure in the appendix 2b shows the distribution of the samples before and after the matching process: in fact in the middle of the figure it is clear to observe that the samples are well balanced.

The proportions observed for the professional status two years after the first interview (or two years after the diagnosis for breast cancer survivors), show important differences between groups: there are about 10 percentage points more employed females in the general population sample (77,6%), whereas on the side of the cancer sample the proportion of the unemployed, retired and inactive females is relatively more important. These observed differences after the matching process are, in fact, the phenomenon in which we are interested: the comparison of the similar groups (in term of the socio-demographic characteristics) suggests that the cancer diagnosed females move more towards unemployment, inactivity and retirement than their counterparts in the general population. The remaining question is whether the temporary separation of the employment (towards unemployment or inactivity) after the breast cancer diagnosis is more probable than the definitive separation (retirement). In fact, the improvement of the diagnosis procedures, the prevention methods and the better care providing extending the life expectancies in that concerning breast cancer make us expect that the employment separations in the cancer group are mostly temporary. From this perspective, two emerging questions are: whether the mobility patterns are different between the cancer survivors and the general population groups; and whether belonging to low or high SES modifies these patterns.

Table 1. Individual characteristics comparison before the matching process

	Cancer survey		Employment survey	
	N	(%)	N	(%)
Total	595		10211	
Age				
Mean (sd)	47,8 (6,809)		42,1 (8,74)	
25th percentile	44		35	
50th percentile	49		42	
75th percentile	53		49	
Married = 1	415	69,7	7063	69,2
At least one child aged of less than 18 years	192	32,7	5105	50
Education level				
Without diploma-primary school	132	22,2	1797	17,6
Secondary school	202	33,9	4802	47
High school	116	19,5	1385	13,6
Higher education[a]	145	24,4	2491	21,8
Professional Status at first interview (time of diagnosis for cancer survivors)				
Employed	462	77,6	6960	68,2
Unemployed	33	5,5	778	7,6
Retired	23	3,9	120	1,2
Inactive	77	12,9	2353	23
Professional Status two years later				
Employed	365	61,3	6987	68,4
Unemployed	55	9,2	614	6
Retired	49	8,2	216	2,1
Inactive	126	21,2	2393	23,4
SES				
Low SES	99	20,0	1701	37,5
High SES[b]	476	80,0	6384	62,5
Urban size				
<100 000 habitants	328	55,1	6240	61,1
>=100 000 habitants	267	44,9	3971	38,9

[a] This category is formed by the following levels: bachelor, master, professional graduate studies, and Ph.D or more.
[b] The low SES category includes: farmers, artisans, factory workers, and drivers. The high SES category includes: top executives, intermediate professionals, and white-collar.

Table 2. Individual characteristics comparison after the matching process

	Cancer survey		Employment survey	
	N	(%)	N	(%)
Total	499		499	
Age				
Mean (sd)	47,5 (6,67)		47,5 (6,64)	
25th percentile	43,0		43,0	
50th percentile	49,0		49,0	
75th percentile	53,0		53,0	
Married = 1	350	70,1	349	69,9
At least one child aged of less than 18 years	161	32,3	162	32,5
Education level				
Without diploma-primary school	109	21,8	115	23,0
Secondary school	184	36,9	185	37,1
High school	83	16,6	82	16,4
Higher education[a]	123	24,6	122	24,4
Professional Status at first interview (time of diagnosis for cancer survivors)				
Employed	425	85,2	422	84,6
Unemployed	14	2,8	18	3,6
Retired	4	,8	4	,8
Inactive	56	11,2	55	11,0
Professional Status two years later				
Employed	336	67,3	387	77,6
Unemployed	37	7,4	20	4,0
Retired	25	5,0	15	3,0
Inactive	101	20,2	77	15,4
SES				
Low SES	96	19,2	98	19,6
High SES[b]	403	80,8	401	80,4
Urban size				
<100 000 habitants	212	42,5	212	42,5
>=100 000 habitants	287	57,5	287	57,5

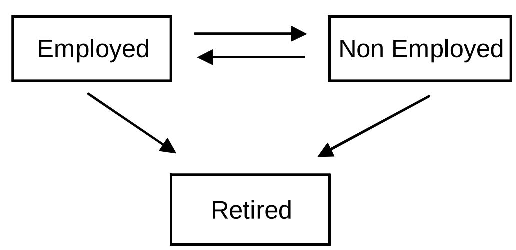
[a] This category is formed by the following levels: bachelor, master, professional graduate studies, and Ph.D or more.
[b] The low SES category includes: farmers, artisans, factory workers, and drivers. The high SES category includes: top executives, intermediate professionals, and white-collar.

3. A continuous-time Markov model for estimating the trajectories in the labor market

In this study where the trajectories of French females are observed in a two-year span, one of the most important obstacles is that the information between two visits is not available. This is not an exclusive feature of our data. In fact, labor market surveys are often confronted to incomplete information (i.e. intermittent follow-up, censored episodes, etc.) It is also difficult to know the exact history of individuals in the labor market. In order to deal with the obstacles imposed by the data and assuming that the evolution of the professional status of females only depends on the state in which they were observed the first time (or at the time of diagnosis for cancer survivors), we use the continuous-time Markov process estimation.

In a recent work, Bosch and Maloney (2007) use average transition matrices and derivative statistics to identify and establish stylized facts about labor force dynamics. These authors use a multi-state model in which individuals can move among five states within the labor market. A more commonly-used model is the "illness-death" model, with three states that represent health, illness, and death. In this study, we use an analogous three-state model (see figure 1) with employment, non-employment (formed by unemployment and inactivity), and retirement as the three possible states within the labor market[2]. The final state also acts as the absorbing, or "death" state. In fact, we assume that individuals in the retirement state never change their status, which is verified by the data we use.

Figure 1. "Illness-death" model



Using the Markov chains, we assume that the future evolution only depends on the current state. If $X(t)$ is a homogenous Markov process defined over a discrete state-space equal to $\{1, \ldots, K\}$, where K is the number of possible states that a worker could occupy, then the discrete-time transition matrix is:

$$P_{ij}(t, \delta t) = \Pr(X(t + \delta t) = j | X(t) = i) \; for \; t = 0,1,2, \ldots and \;\; \delta t = 0,1,2 \ldots \qquad (1)$$

The last equation represents the probability of moving from the state i to state j in one period (δt). The next state to which the individual moves and the time of the change are governed by a set of transition intensities $q_{ij}(t, z)$ for individual characteristics that do not vary with time,

2 Initially, we specified a model with four states (employment, unemployment, inactivity, and retirement), but the small number of observations in the inactivity state prevented convergence at the time of the estimation. Thus, we have decided to merge unemployment and inactivity states in a single state named "non-employment."

captured by the variable z. The (kxk) transition intensity matrix Q is formed by the instantaneous risk of moving from state i to state j:

$$q_{ij}\big(t, z(t)\big) = lim_{\delta t \to 0} \frac{P(X(t+\delta t)=j|X(t)=0)}{\delta t} \tag{2}$$

The two main restrictions are first that the rows of the Q matrix sum to zero, and second that its diagonal entries are defined by $q_{ij} = \sum_{i \neq j} q_{ij}$. Thus, if $dP(t)/dt = QP(t)$, the solution is given by:

$$P(t) = e^{tQ} \tag{3}$$

In order to estimate the matrix Q, Kalbfleisch and Lawless (1985) used a quasi-Newton algorithm. Their maximum likelihood procedure approach establishes that the inference will be not reliable if the matrix P is not embeddable. In this case, standard asymptotic theory does not apply[3]. However, many conditions have been proposed to verify the embeddability of P-matrices. Unfortunately, for multi-state models with more than two states, only the necessary conditions for the embeddability of P are known[4]. Following Fougère and Kamionka (1992), once we estimate $\hat{P}(t)$, we then verify the following properties:

$\forall i, j = 1,2,3, \hat{p}(t) \neq 0; \hat{P}(t)$ allows $K = 3$ values $\lambda_1, \lambda_2, \lambda_3$, real, positive, different, such as $|\lambda_i| \leq 1, \forall i = 1,2,3$ where λ_i are the diagonal entries of the Q matrix; there is a unique solution $\hat{Q}$ to the equation (3).

Given the objective of this paper, which is to study the impact of a chronic disease on the mobility between employment, non-employment and retirement, we will introduce a non-time-varying explanatory variable z. The transition intensity matrix elements depend on z in the following way:

$$q_{ij}(z) = q_{ij}^{(0)} \exp\,(\beta_{ij}' z) \tag{4}$$

The new matrix Q is then used to determine the statistical likelihood[5].

The delta method used in the estimation by maximum of the log-likelihood allows us to estimate the asymptotic standard errors for the intensity matrix[6]. However, for $\hat{P}(t)$, the delta method cannot be used to obtain standard errors. Additionally, the asymptotic standard errors are expected to be underestimates of the true standard errors; that is, they act as Cramer-Rao lower bounds. Therefore, we estimate the different matrices using the bootstrap technique,

3 In practice, there are two main problems in the estimation of the continuous time transition matrix, namely the aliasing and the embeddability problems. The former implies the impossibility of finding a unique solution for the equation (3). That means the possible existence of more than one underlying continuous matrix that generates the observed discrete-time matrix. Secondly, the embeddability problem is in fact the incompatibility between the theoretical model and the solutions obtained for the matrix Q; the elements of the latter must satisfy the restrictions enumerated above. See singer and Spilerman (1976) and Geweke *et al.* (1986) for a detailed list of necessary conditions for the embeddability of P.

4 The only necessary and sufficient condition that has been proposed for two-state P-matrices is as follows: the estimation of the transition probability matrix is compatible if and only if the trace of $\hat{P}(t)$ is strictly greater than one.

5 See the work of Marshall and Jones (1995) for further information about the covariates specification.

6 The estimated variance-covariance matrix is derived by applying the multivariate version of the delta theorem (Kalbfleisch and Lawless, 1985).

calculating the bootstrap standard error (Bosch and Maloney, 2007). For that purpose, we replicate the estimation 10,000 times.

4. Results

In this section we describe the continuous-time Markov process estimations that generated transition matrices for different groups. First, we present the transition matrix including as covariate a dummy variable indicating whether the female has or not been diagnosed with breast cancer. The second part or our results is made using a twice-stratified sample. We first distinguish diagnosed females from those who are not. Then, we stratify according the low and high socioeconomic status groups (by SES). Given the objective of this study, in this section we only present the estimations of the probability transition matrices.

4.1 The impact of the breast cancer diagnosis on the mobility in the labor market

Table 3 shows the estimated probability transition matrices for both diagnosed and non-diagnosed groups. First of all, we observe that remaining employed within the observed two-year period is more likely for individuals without cancer. In fact, the probability of being employed two years after the first observation is around 90% for the non-diagnosed females, while the chances to remain employed at the end of the observation period is only 78,6% for females surviving to the breast cancer. In fact, the breast cancer diagnosis seems to induce the females to leave their employment mostly towards the NE state: the probability of the E-NE transition two years after the diagnosis is more than 2 times higher than the one observed for non-diagnosed females. These results suggest that the breast cancer does not induce females to leave definitively the labor market by the way of the retirement, although retiring is more probable for diagnosed females (4%) than for non-diagnosed (1,3%). In that concerning the access into employment, the NE-E transition appears slightly more probable for the females without breast cancer (8%) than for those diagnosed (5,6%). Nevertheless, the most important feature concerns the decision of going towards retirement from non-employment (NE-R transition). Our estimations reveal that the breast cancer diagnosis is not at the origin of an increase of the probability of retiring. In fact, it is relatively more probable to go towards retirement for non-diagnosed females (6,8% versus 5% for diagnosed females). The remaining question is whether the estimated probabilities evolve beyond the 2 years of observation.

Table 3. Transition probability matrices for both non-diagnosed and diagnosed females (Balanced samples: N=998)

		No cancer diagnosed (n=499)				Cancer diagnosed (n=499)		
		Final state 2 years after the first observation						
		E	**NE**	**R**		**E**	**NE**	**R**
Initial state	**E**	0,904	0,083	0,013	**E**	0,786	0,173	0,040
		0,001	*0,001*	*0,000*		*0,001*	*0,001*	*0,000*
	NE	0,080	0,851	0,068	**NE**	0,056	0,894	0,050
		0,001	*0,002*	*0,001*		*0,001*	*0,002*	*0,002*
	R	**Absorbing state**			**R**	**Absorbing state**		

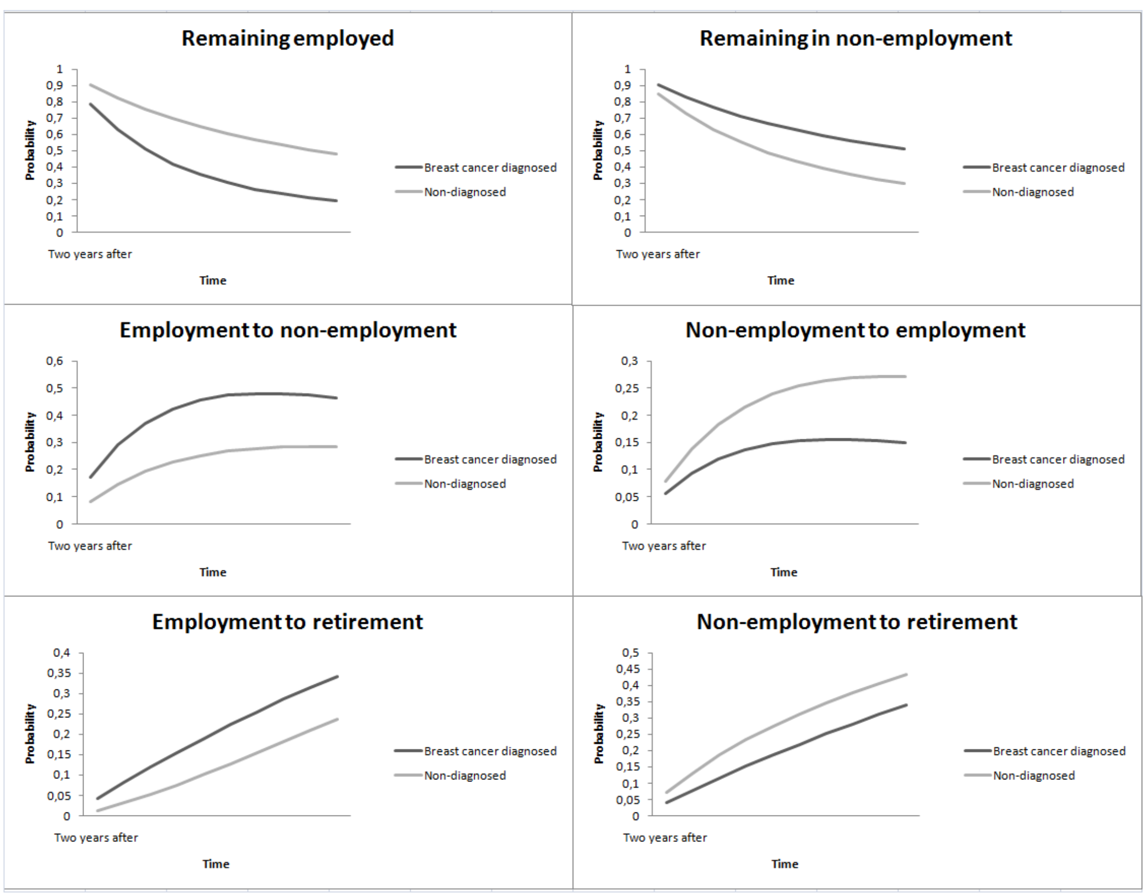
Standard errors are in italics.
E: employment, NE: non employment, and R: retirement.
Our bootstrap estimations are based on 10000 replications.
Non employment includes unemployment and inactivity.

One of the advantages of the continuous-time Markov method is that we can use the estimations based in the observed period to predict the probabilities for future periods. Assuming that the future social and economic conditions are similar to those at the observed period, we estimate the transition probabilities for different time's point in the future. We carry out this simulation in order to observe ceteris paribus the evolution of the different transition probabilities for both diagnosed and non-diagnosed groups of individuals.

Figure 2 shows the probabilities of moving between the states considered in this study. The first column of figures represents the transitions from the employment (E), whereas in the second column of figures the state of origin is the non-employment (NE). In these figures, the gap between the lines represents the impact of the breast cancer diagnosis on the different types of mobility. The probability of remaining employed decreases for both diagnosed and non-diagnosed groups: in fact, the breast cancer seems to accelerate this reduction. The situation is similar for the probability of remaining into non-employment although the highest probabilities are associated to the females diagnosed with breast cancer. The transitions between E and NE in both directions show similar patterns although the access into employment is more probable for non-diagnosed females, whereas becoming non-employed is more probable for females diagnosed with breast cancer. Nevertheless, the transitions between of the type E-NE show an important feature. The simulated probabilities are increasing until a given point in time, and then decreases. It seems that in the long run, the breast cancer survivors and the non-diagnosed females experience similar probabilities of moving between employment and non-employment. In that concerning the transitions towards retirement, we observe that two years after diagnosis the probability is similar between both diagnosed and non-diagnosed groups. Nevertheless, the slope of the curve representing the diagnosed females becomes more pronounced. That is, the probability of becoming retired is relatively high for cancer survivors.

Summarizing, the simulated probabilities suggest that the impact of the breast cancer diagnosis persists in the long run for remaining employed or non-employed as well as for moving towards retirement: the gap between the corresponding curves persist as the time goes by. On the contrary, it seems that the effect of the breast cancer diagnosis tends to disappear in the long run particularly for the E-NE transition. Although the simulated probabilities show well the impact of the breast cancer diagnosis on the mobility across the different states, it seems that the described patterns are mostly related with the socio-demographic characteristics of individuals. It is important to take into account that the mean age of both the diagnosed and the non-diagnosed groups is 47,5 years. The simulated probabilities involve an ageing effect that seems to be dominating the described patterns. These last seems to be mostly reflecting the life cycle of females in the labor market: that is, the probability of remaining employed or non-employed converges to zero (individuals leaving the labor market), and we could expect that the movements between E and NE in both directions will result in an inverse U-shaped form showing that the labor market becomes less dynamic after a given point in time. This is confirmed by the pattern of the probabilities of going towards retirement, which increases monotonically. Our results in this part of the analysis showed that the breast cancer diagnosis has a negative impact for remaining employed and for returning to work. Nevertheless, several studies including the one of Spelten *et al.*, (2002) argue that effectuating manual and physical-demanding activities (low SES) are at the origin of weak probabilities for remaining employed or for returning to work. From this perspective, we could expect that belonging to a high SES attenuates the effects of the breast cancer diagnosis on the probabilities of moving across the considered states (or remaining in the same state). But, is the effect of high SES enough to erase the one of the breast cancer diagnosis? The estimations in the next sub-section will shed some light about this fact.

Figure 2. Evolution of the probabilities of moving between employment, non-employment and retirement



4.2 Breast cancer diagnosis vs. socio-economic status

The table 4 shows the probability matrices estimation for both diagnosed and non-diagnosed groups stratified according low and high SES. Comparing the groups horizontally, we find the expected order indicating that the females in the low-SES category are less likely to remain employed than those in the high-SES category. Nevertheless, the effect of the SES is more pronounced among the breast cancer diagnosed: the probability of remaining employed for those in high-SES is 8 percentage points more important than the one for low-SES workers (within the non-diagnosed groups the difference is only of around 4 percentage points). It is surprising to observe, on one hand, that the access into employment probability is quite similar for both low and high SES groups among the cancer diagnosed (around 5,5%). On the other hand, leaving the employment by recalling into unemployment or inactivity (NE) is more probable for low-SES workers particularly those diagnosed with breast cancer: for these last, the probability of effectuating a transition of the type E-NE is 10 percentage points higher than the one estimated for the diagnosed females in high-SES.

The vertical comparison of the groups in the table 4 shows that the effect of the cancer diagnosis remains important even by stratifying the samples by SES. Within the low-SES group, the diagnosed females are much less likely to remain employed (with a probability of 71,6%), than their non-diagnosed counterparts (whose probability is 86,3%). On the contrary, the former are much more likely to go towards non-employment (26%) than the latter (13%). In that concerning the non-employed at the initial observation, the cancer diagnosis effect seems not very important among the low-SES workers. The vertical comparison for the high-SES group offer similar features.

Table 4. Transition probability matrices for both non-diagnosed and diagnosed females (Balanced samples: N=998)

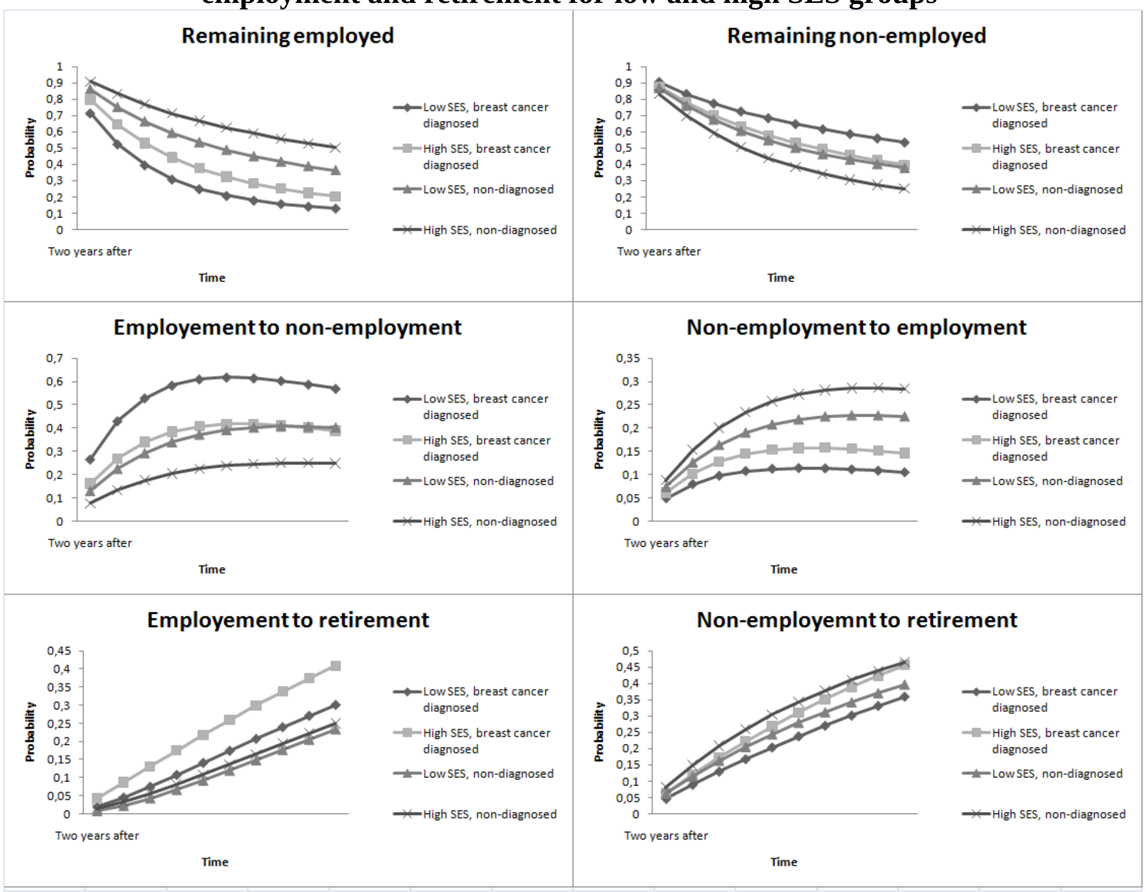
		Low SES no cancer diagnosed (n=98)				High SES no Cancer diagnosed (n=401)		
		Final state 2 years after the first observation						
		E	**NE**	**R**		**E**	**NE**	**R**
Initial state	**E**	0,863	0,130	0,007	**E**	0,908	0,078	0,014
		0,003	*0,003*	*0,000*		*0,001*	*0,001*	*0,000*
	NE	0,067	0,874	0,059	**NE**	0,099	0,808	0,093
		0,003	*0,004*	*0,003*		*0,003*	*0,004*	*0,003*
	R	**Absorbing state**			**R**	**Absorbing state**		

		Low SES breast cancer diagnosed (n=96)				High SES breast cancer diagnosed (n=403)		
		Final state 2 years after the first observation						
		E	**NE**	**R**		**E**	**NE**	**R**
Initial state	**E**	0,716	0,261	0,023	**E**	0,796	0,165	0,039
		0,005	*0,005*	*0,002*		*0,001*	*0,001*	*0,001*
	NE	0,057	0,895	0,048	**NE**	0,054	0,858	0,088
		0,004	*0,006*	*0,004*		*0,001*	*0,005*	*0,004*
	R	**Absorbing state**			**R**	**Absorbing state**		

Standard errors are in italics.
E: employment, NE: non employment, and R: retirement.
Our bootstrap estimations are based on 10000 replications.
Non employment includes unemployment and inactivity.

Although our estimations show that the effect of the SES is the expected one: high-SES workers remains more into employment and go less towards non-employment, it is difficult to observe the extent in which the SES attenuates the impact of the cancer diagnosis. In order to observe this, the figure 3 shows the simulated probabilities for the different groups. First of all we observe that the most vulnerable group in that concerning the mobility between E and NE in both directions (and staying in them) is the one of diagnosed females in the low-SES. The females diagnosed in low-SES are the most (less) likely to remain employed (non-employed). In that concerning the mobility between the E and NE in both directions, these females (diagnosed in low-SES) are still the most vulnerable of the labor market. Similarly, the females not diagnosed in high-SES appear as the group with the best position in the labor market: easier access to employment, less separation from employment and high (low) probabilities of remaining employed (non-employed). For remaining employed and moving from NE to E the cancer diagnosis seems to be the dominating effect. Nevertheless, for remaining non-employed and moving from E to NE the SES seems to be modifying the effect of the breast cancer diagnosis. For these cases, the probabilities of diagnosed females but in high-SES are similar to those of non-diagnosed females but in low-SES. This result points out that the breast cancer diagnosis is a degrading factor of the situation of high-SES females: these last are as likely as the low-SES females (not diagnosed) for leaving employment and for remaining non-employed. Finally, we observe at the bottom of the figure 4 an asymmetric pattern between the employment and the non-employment in that concerning the transition towards retirement. On one hand, the cancer diagnosis effect dominates the one of the SES: females are more likely to go towards the retirement when the initial state is the employment. On the other hand, the SES is the dominating effect: the high-SES individuals are more likely to become retired when the initial state is the non-employment. This result proves that the breast cancer diagnosis accelerates the process of early retirement for employed survivors.

Figure 3. Evolution of the probabilities of moving between employment, non-employment and retirement for low and high SES groups



Discussion

In this study, we examined the impact of breast cancer on transitions between employment, non-employment and retirement two years after diagnosis. Among breast cancer survivors who were employed at the time of diagnosis, 80% remain at work two years later, which is in line with previous studies (Maunsell et al. (2004), Bloom et al. (2004), Bushunow et al. (1995)). This can be explained by the fact that female affected by breast cancer recover a good health status relatively quickly. This is confirmed by our data which show that the relative prognosis at the time of diagnosis of breast cancer is 72 (in a scale from 0 to 100). This is a high relative prognosis if we consider that the one for other types of cancer is from 29 (for lung cancer) to 64 (for prostate cancer). Women diagnosed with breast cancer show higher transition probabilities of moving from employment to non-employment or retirement than females without cancer. Our results are in line with Taskila et al. (2005), who noticed that unemployment or early retirement was common among people with breast cancer two or three years after diagnosis; even if the labor situation is worst for those with a highly disabling cancer of poor prognosis.

We identified some studies using a control group to study unemployment of breast cancer patients (Taskila et al., (2005); Maunsel et al., (2004); Bradley et al., (2005); Carlsen et al., (2008)). However, except the work of Bradley et al., (2005), the case-control matching is based on two or three individuals' characteristics. One of the main innovations of this study is the use of many control variables to create the comparison group. In fact, the introduction of more socio-demographic characteristics as the criteria to match the two samples increases the robustness of the final results. Specificity is the use of the continuous-time Markov chains in this context.

The study of the mobility in the labor market of breast cancer diagnosed females also revealed that those non-employed at the time of diagnosis were only 4 percentage points more likely to be in the same state two years after than the non-diagnosed females. These results are in agreement with the findings of Bradley et al. (2005) who studied persistence of unemployment among female diagnosed with breast cancer. Nevertheless, the most important effect of the breast cancer diagnosis among French females is observed on the probability of remaining employed two years after. This situation persists after distinguishing between low and high SES particularly for the former.

Our results also show that there is an important incentive for old patients of leaving the labor force by appealing to their right of early retirement. Nevertheless, the access to the early retirement reveals an asymmetrical pattern according to the initial state. Employed females are more likely to retire when they are breast cancer survivors, whereas those non-diagnosed females are more likely to retire when they are non-employed. The illness event seems to induce patients to leave the work force especially for high-SES workers. This decision could either improve or worsen health. In fact, the opinions are divergent: for some authors, early retirement leads to a better health condition (J.R. Wolfe (1985)), although « physical and intellectual stimuli of job may improve health » (Mc Garry (2004)). The reason to take early retirement, as reported by many studies, is explained by poor health. As this explanation is based on self-reported answers, some authors refer to the "justification bias", i.e. individuals justify retirement by a health problem because it's a more socially acceptable explanation, even if it's untrue (Campbell and Campbell (1976), J. R. Wolfe (1985)). Early retirement is a crucial decision because of the financial difficulties coming with the illness. The income loss is especially increased because breast cancer represents an unexpected change in health. Without anticipation, the beneficiary will receive a lower retirement income compared with the one who has planed his early departure and adapted his savings to compensate the future shortfall (Mc Garry (2004)). Thus early retirement has economical, societal and physical implications.

Given the importance of socioeconomic status with regard to the probability of job loss, Taskila-Abrandt et al. (2004) found the largest differences in employment rates among people working in mining and agriculture, forestry, fishery, transport, and communication, all of which are mostly manual jobs, as compared with other types of work. This is consistent with our results. However, we note the difficulty in disentangling whether these observed systematic differences along socioeconomic statuses are illness-related (such as cancer sites or severity of the illness) or job-related (such as physical demands). Thanks to our methodology, the main contribution of this paper is that a decomposition of both sources of heterogeneity is now possible. It is well know that the ability to return to work or remaining employed has an epidemiological basis. Nevertheless, our study contributes principally by demonstrating that the differences between diagnosed and non-diagnosed females have also an economic explanation. The probability of being employed two years after diagnosis is the weakest for low-SES females. This is a net measurement of the relative disadvantage of manual workers and farmers in returning to work after cancer in contrast to high-SES individuals. In addition we showed with our estimations that the breast cancer diagnosis is a deteriorating factor of the conditions that high-SES workers have in the labor market. There are many explanations for the differences between the SES groups according to their health status –in this case the breast cancer-. One explanation could be that the French social protection system gives rights to a replacement income or invalidity pension that could be, at least for low-skilled professionals, as attractive as returning to work. Another explanation may lie in the fact that workplace accommodations are especially difficult to make when labor is manual (Molinié, 2006; Satariano and DeLorenze, 1996). Regardless, the results of this paper suggest that policy-makers should be specifically concerned about manual workers affected by cancer. Without attention from policy-makers, both the general employment policy and the health protection system could be overwhelmed by the phenomenon detailed in this paper. The economic policy should also screen the situation of high-SES workers in that concerning the separation from employment. For these females, experiencing a breast cancer episode may result in a regressing situation which places them at the same level of a low-SES female without cancer.

References

Bloom, JR., Stewart, SL., Chang, S., Banks, PJ, 2004. Then and now: quality of life of young breast cancer survivors. Psycho-oncology 13, 147-160.

Bradley, C.J., Bednarek HL, (2002). Employment patterns of long term cancer survivors. Psycho-oncology 11, 188-198.

Bradley, C.J., Neumark, D., Bednarek, H.L., Schenk, M., (2005). Short-term effects of breast cancer on labor market attachment: results from a longitudinal study. Journal of Health Economics, 24(1); 137-160.

Becker, S., Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. The Stata Journal, 2 (4), 358-377.

Bloom JR, Stewart SL, Chang S, et al. (2004). Then and now: Quality of life of young breast cancer survivors. Psychooncology 13:147-160.

Bosch, M., Maloney, W., (2007). Comparative analysis of labor market dynamics using Markov processes: an application to informality. IZA Discussion papers 3038,Institute for the study of labor.

Bushunow PW, Sun Y, Raubertas RF, et al. (1995). Adjuvant chemotherapy does not affect employment in patients with early-stage breast cancer. J Gen Intern Med 10:73-76.

Carlsen, K., Oksbjerg Dalton, S., Diderichsen, F., Johansen, C., (2008). Risk for unemployment of cancer survivors A Danish cohort study. European Journal of Cancer, 44(13); 1866-1874.

Chirikos, T.N, Russell-Jacobs, A., Jacobsen P.B, (2002). Functional impairment and the economic consequences of female breast cancer. Women's Health 36, 1-20.

Fougère, D., Kamionka, T., (1992). Un modèle markovien du marché du travail. Annales d'Economie et de Statistique. 27, 149-188.

Greaves-Otte, J.G., Greaves, J., Kruyt, P.M., Van Leeuwen, O., Van Der Wouden, J.C, Van Der Does, E, (1991). Problems at social reintegration of long-term cancer survivors. European Journal of Cancer 27, 178-81.

Hoffman, B., (1999). Cancer survivors' employment and insurance rights: a prime for oncologists. Oncology (Williston Park)13, 841-6; discussion 846, 849, 852.

Hoffman, B.,2005. Cancer survivors at work: a generation of progress. CA Cancer J Clin 55, 271-80.

Johnson R.W., Davidoff A.J., Perese K., (2003). Health insurance costs and early retirement decisions. Industrial and Labor Relations.

Kalbfleisch, J.D., Lawless, J.F., (1985). The analysis of panel data under a Markov assumption. Journal of the American Statistical Association. 80, 863-871.

Maunsell, E., Brisson, C., Dubois, L., Lauzier, S., Fraser, A., (1999). Work problems after breast cancer: an exploratory qualitative study. Psycho-oncology 8,467-473.

Maunsell E, Drolet M, Brisson J, et al. (2004). Work situation after breast cancer: Results from a population-based study. J Natl Cancer Inst 96:1813-1822.

McGarry K., (2004). Health and retirement: do changes in health affect retirement expectations? The Journal of Human Resources.

Schagen, S.B., van Dam, F., Muller, M.J., Boogerd, W., Lindeboom, J., Bruning,P.F, 1999. Cognitive deficits after postoperative adjuvant chemotherapy for breast carcinoma. Cancer 85, 640-650.

Short, P.F., Vasey, J.J., Tunceli, K, (2005). Employment pathways in a large cohort of adult cancer survivors. Cancer. 103, 292-301.

Spelten E.R., Spranger, M.A.J., Verbeek, J., (2002). Factors reported to influence the return to work of cancer survivors: a literature review. Psycho-oncology. 11,124-131.

Taskila-Abrandt,T., Pukkala, E., Martiikainen, R., Karjalainen, A., Hietanen, P., (2005). Employment status of Finnish cancer patients in 1997. Psychooncology, 14(3); 221-226.

Appendix 1: Propensity score matching

a) Introduction

The comparison of two groups is often necessary to highlight a particular behavior within a group of interest. It is current that significant differences appear among the characteristics of the compared individuals. Therefore, there exists a skew of selection and the inference of the possible results would be wrong. Similar groups (comparable) are needed: it can be done by matching individuals of the group of interest with the group used to compare them. Matching is based on some individual characteristics. A refined method is the creation of a propensity score to summarize the various characteristics in one single outcome.

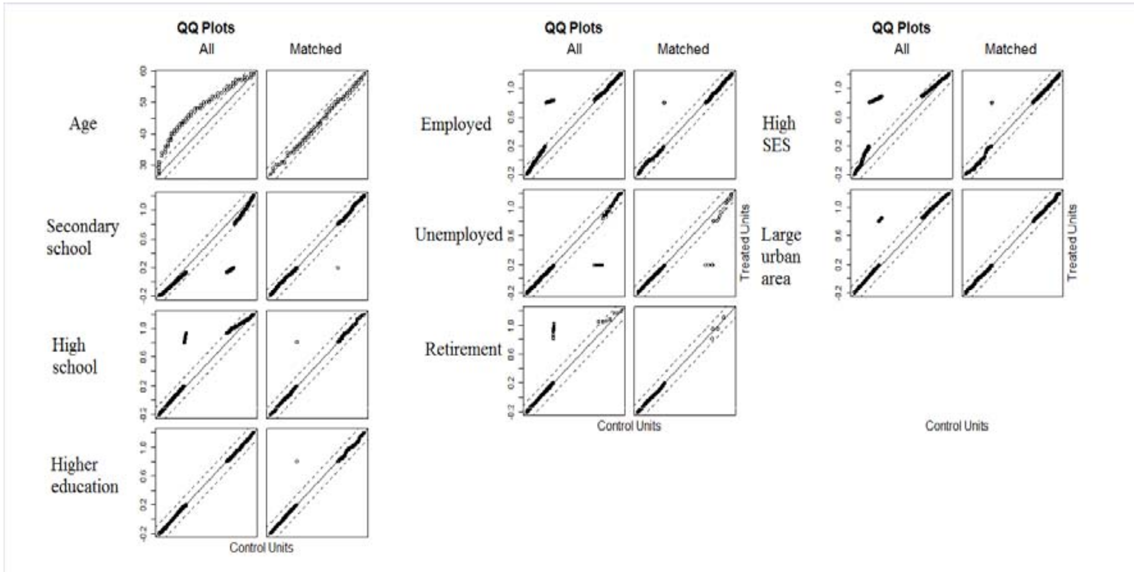
b) General aspects of the method

The aim of matching is creating two groups (diagnosed / non-diagnosed) of individuals closest as possible in term of socioeconomics characteristics. Matching is used to compare two groups. This technique applies if the control group is larger than the case group. This technique is more useful when selection depends only on observable characteristics. For instance, if the matching variable is "to have or not a breast cancer", constructing pairs only on socioeconomics variables seems reasonable because the knowledge on the link between these variables and the risk of having breast cancer is weak. The built sample supposes that the individuals follow a binomial distribution, i.e. by construction same probability of being in the interest group and in the group of control. The skew of selection between the two matched groups is reduced. However, the method of sampling used force the control group not to be representative of its sample of origin: the results obtained are not representative of the general population, but allows the comparison with the sample of interest (in our case the breast cancer diagnosed females).

c) Propensity score (Rosenbaum et Rubin, 1983)

Let i denote the group of breast cancer survivors, and j the group issued from the general population. The *propensity score* matching technique consists in the estimation of the probability of belonging to breast cancer group. This probability can be estimated from a Logit or Probit specification: the interest is thus to estimate the probabilities p_i and p_j on the basis of the observed characteristics common to both the breast cancer and the general population groups. It is important to note that the choice of covariates has to take into account that the presence of missing values may result in the failure of the matching. In our study, we chose the "nearest neighbor" algorithm by setting a Caliper criterion equal to 0,0001. That is, the breast cancer-general population pairs will be created if the $|p_{i-}p_j| < 0{,}0001$. The algorithm is stopped when there are no more possible pairs.

Appendix 2a.



Appendix 2b.