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Health condition and job status interactions: Econometric evidence of causality from a French longitudinal survey

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Health condition and job status interactions: Econometric evidence of causality from a French longitudinal survey

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Abstract

This article investigates the causal links between health and employment status. To distangle correlation from causality effects, the authors leverage a French panel survey to estimate a bivariate dynamic probit model that can account for the persistence effect, initial conditions, and unobserved heterogeneity. The results highlight the crucial role of all three components and reveal strong dual causality between health and employment status. The findings clearly support demands for better coordination between employment and health public policies.

Keywords: health and job causality, bivariate dynamic probit model, Gauss-Hermite method

JEL Classification: I10, J6, C3, C51

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Introduction

Both health changes and labor market instability have important impacts on individual well-being, which strongly guides policy makers in defining rules for health insurance, unemployment benefits, and or retirement. Substantial empirical literature stresses the links between health and labour market risks, yet the precise relationship between the two phenomena remains unclear, leaving the definition of appropriate public policies uncertain as well, especially because policies in the labour market can produce health effects (and vice versa).

Early empirical studies focused on one-way causality, such that health conditions explained labour market transitions or *vice versa*. For example, in Berkowitz and Johnson's (1974) pioneering study, people's health determines their labour participation decisions, and Stern (1989) confirms that disabilities strongly affect labour participation. As an endowment of human capital, health determines productivity and preferences for work between leisure (Grossman, 1972). Moreover, two complementary results emerge from a literature review (Currie and Madiran, 1999). First, poor health affects everyone's labour choices, but the impact is especially powerful among the elderly, such that health problems significantly increase choices to retire (Sickles and Taubman, 1986; Bound, 1991; Cai and Kalb, 2006,2007; Christensen and Kallestrup-Lamp, 2012), and retirement decisions often represent an attempt to preserve health (Coe and Zamarro, 2008). Second, the impact of a person's health varies with the type of health deterioration. Chronic diseases, such as cancer (Eichenbaum-Voline et al., 2008), diabetes (Bastida and Pagan, 2002; Brown et al., 2005), mental illness (Butterworth et al., 2006), and disabilities (Stern, 1989), seem to have the strongest effect on individual transitions in the labour market.

In addition, employment status has implications for health. For example, unemployment and inactivity slightly increase the risks of cardiovascular diseases (Jin et al., 1995), cancer, or mental illnesses (Brenner, 2002, Llena-Nozal, 2009). Morris et al. (1994) using British data and Mathers and Schoflied (1998) using Australian data confirm that a loss of employment increases mortality risk. Mesrine (2000) shows that this impact is even greater following long spells of unemployment. The pecuniary and non-pecuniary effects of inactivity and unemployment on health help explain these empirical findings. Unemployment usually decreases the health care resources available to the person, so it can affect health over the long-term.

In addition, unemployment and non-participation in the labour market damage peoples' self-esteem (Brenner, 2002; Llena-Nozal, 2009) and decrease their sense of well-being (Winkelman and Winkelman, 1998; Clark et al. 2001). Persistent unemployment and inactivity thus create threatening conditions for health. Conversely, being employed can have some deleterious effects on health, such as by increasing the risk of stress, professional illness and work accidents. Thus, Debrand (2011) uses economic data to argue that bad working conditions and work pain cause damage to people's health. Using a matching approach with the French Health Survey 2002, Debrand shows that workers exposed to poor working conditions consult physicians 25% more than those who are not. Hamon-Cholet and Sandret (2007) similarly find, with French data, that noisily jobs increase the professional accident rate to 25%.

However, the links between health and labour status may be more complex than a one-way form of causality. Recently, some authors have emphasized the need to correct for endogeneity between health (Madden, 2004; Brown et al., 2005; Haan and Myck, 2009) and labour market transitions (Rietveld et al., 2015). Neglecting endogeneity can cause strong estimate biases. For example, Caroli and Godard's (2014) analyses of the European Working Conditions data set indicate that the fear of involuntary job loss can affect health measures, such as headaches, eye-strain, and skin problems. Without controlling for the endogeneity of job insecurity, job insecurity degrades all health indicators. This endogeneity of health and job risks likely reflects two main sources. First, unobserved heterogeneity, such as that due to lifestyle or individual preferences, can influence both health and labour market processes (Cai, 2010). Second, measurement errors in self-reported health surveys or using poor health as a reason to justify unemployment, might create substantial endogeneity biases (Zhang et al., 2008).

Another major source of endogeneity is likely reciprocal: Labour activities and health affect each other. Few studies take this simultaneity into account, though Haan and Myck (2009) propose a bivariate model with a lagged dependent variable to analyze dynamics in health and labour market risk. This approach offers the advantage of addressing endogeneity problems and allowing for a dynamic analysis. Accordingly, these authors show that recent health conditions affect current labour market risk, and vice versa, and that this dynamic is strongly persistent. Such persistence effects also may be due to favorable or unfavorable initial conditions for health and employment (Heckman, 1981; Arulampalam and Stewart, 1995), and Haan and Myck (2009) do not address these potential contingencies. Neglecting these initial conditions could bias estimates of the simultaneity effect between health and employment status.

Finally, we lack clear definitions of all the links between health and job risks. With this article, we propose an innovative methodology for identifying and assessing all the complex links between health and employment paths. With our modeling approach, we can jointly estimate the two phenomena. We assume sequential causality, as in Alessie et al. (2004) or Haan and Mynck (2009), such that the most recent health status can influence the current labour market status, and the last event in the labour market affects the current period health status. We also account for unobserved heterogeneity and persistence in the two processes over time (Adams et al., 2003). Finally, following Wooldridge (2005), we control for initial conditions.

Unlike previous empirical works, we aim to establish whether there true causality exists between health and employment, as well as to define its meaning and scope , such that we can derive insights and guidance for economic policies. If health and employment are independent, policy makers can use disconnected instruments. If single causation exists instead (e.g., job transitions explain health paths but health does not affect job risks), it will be necessary to monitor the effects of an employment-centered policy on health. Finally, if dual causality exists, only the joint definition of health and employment policies can improve health and employment.

The estimates in this study feature a sample of French individuals who completed the Santé et Itinéraire Professionnel (SIP) survey (DARES, DREES, 2006). This survey (see Section 1) indicates, for each year since the participant finished school until 2006, all individual events related to health and labour market status. With this long panel data, we can better control for unobserved heterogeneity compared with using cross-sectional data. Moreover, this survey provides empirical evidence of the links between health and labour market paths in France, whereas prior literature has focussed on U.S., British, or Australian data. Significant institutional differences (in terms of legislation regulating the labour market and rules governing health systems) exist across these countries, which limits the generalizability of the results obtained in English-speaking countries to the French case. Focusing on the French case thus might provide new insights and clarify the links between health and labour market transitions, by addressing them in a different kind of the health care system.

Section 1 presents the relevant data for this analysis. Section 2 outlines the innovative methodology we have implemented to investigate the complex links between health and labor market transitions. After we present and discuss the results in Section 3, we conclude with some implications and directions for further research.

1 French longitudinal survey on health and work: SIP

Conducted in 2006 by DARES[1] and DREES[2], the Santé et Itinéraire Professionnel (SIP) survey gathered information about 13,991 individuals, aged from 20 to 74 years (Mermilliod, 2012). This survey describes individual paths on the job market and health status. Each respondent provides the information about previous conditions. The survey data also include socioeconomic information, such as gender, age, grades, income, and ethnicity.

Because we seek to analyze events during people's professional lives, we exclude those who never entered the job market. We also exclude those who entered before 1962, to observe macroeconomic conditions that may affect individual transitions in the labour market. After dropping observations with missing data, we obtained a sample of 10,569 persons who provided detailed information about their participation in the labour market and their health status, spanning the full professional path of each individual, from the end of schooling to retirement. On average, each respondent thus provides information about a period of 26 years[3]. Pooled produce 255,206 observations.

For each year of professional life, we identify job status according four categories:

[1]Direction de l'Animation de la Recherche, des Etudes et des Statistiques, the statistical bureau of the French administration for Labor Affairs.

[2]Direction de la Recherche, des Etudes, de l'Evaluation et des Statistiques, the statistical bureau of the French administration for Health Affairs.

[3]Excluding the initial lagged period.

- Long time period employments, which last at least five years.
- Short time period employments, which last less than five years.
- Unemployment periods, which last more than one year.
- Out of job market time periods, which last more than one year.

With the first two items, we define all respondents who report being employed in a long-term or short-term job as employed for that given year. Our definition of employed people is thus quite expansive, because non-employment status covers both unemployment and non-participation. In addition, the SIP survey does not offer a means to observe short-term (shorter than one year) unemployment or inactivity. Being employed during a particular year in the survey does not imply that individuals were employed for the entire year though, so measurement errors could arise labour market status variable. To avoid this bias, and as robustness tests, we also consider long-term inactivity and unemployment status. These two items also are binary variables, equal to 1 if the respondent is inactive or unemployed for the entire given year.

Moreover, participants self-report whether they have encountered illnesses during a given year. With these data, we can construct a health indicator as a binary variable, equal to 1 if the respondent reports any illness. For a better understanding of health status, we also create a more qualitative indicator, similar to Christensen and Kallestrup-Lamp (2012). For each illness reported in the survey, we know the corresponding World Health Organization's ICD[4]. That code also reveals an indicator of severity and an indicator of disability according to the mapping created by the Institut de Recherche et de Documentation en Économie de la Santé (IRDES). The severity index indicates if the illness is related to a risk of death; the disability index determines if the illness affects the person's daily life. With these information, we create binary dummy variables to establish when the risk of death is large (`rdeath=1`) and when the disability index is large (`disab=1`). In turn, we create a percentage measure to reflect the extent to which each situation occurs over the course of the respondent's full working life.

[4]International Statistical Classification of Diseases and Related Health Problems - 10th Revision (ICD-10)

Because we know the length of each respondent's professional life, we can calculate synthetic indicators of the professional and health paths: the percentage of professional life with at least one illness and the share of employment, unemployment, and out-of-job market periods in professional life (see Table 1).

Table 1: Descriptive statistics for labour market and health paths

Number of years per individual	26.994	12.070
Share of employment periods in professional life	0.863	0.237
Share of unemployment periods in professional life	0.034	0.093
Share of out-of-job market time periods in professional life	0.103	0.219
Share of years with at least one illness in professional life	0.1795	0.295
Share of years with at least one illness with disability	0.019	0.165
Share of years with at least one illness with risk of death	0.028	0.135

Notes: Number of individuals: 10,569

As this table shows (means in column 2 and standard deviations in column 3), employment periods represent a large fraction of the professional life. Only 3.4% of professional life involved long-term unemployment, and 10.3% occurred out of the job market. Illness periods represented almost 18% of the professional life.

Moreover, exploiting the longitudinal dimension of our data, we examine the conditional outcome in period t, conditional on the respondents' self-assessed statuses in the labour market and health in period $t-1$ (Table 2). We find considerable persistence in both the labour market and health paths. For example, conditional on being employed in $t-1$, about 97.8% of respondents report being employed in t (on pooled sample).

Table 3 presents the labour force status against lagged self-reported health, using the pooled sample.

It highlights the negative relationship between poor health and employment. Respondents who declare a disease in $t-1$ are more likely to be unemployed or out of the labour market in t. But these statistics also suggest evidence of a reverse link, as suggested in prior literature. Table 4 presents the health status against the lagged labour market indicators, using the

Table 2: Transitions in labour market and health status

	Status in t					
Status in $t-1$	Employed	Unemployed	Out of labour market	Ill	Ill with disability	Ill with risk of death
Employed	0.978					
Unemployed		0.761				
Out of labor market			0.921			
Ill				0.986		
Ill with disability					0.929	
Ill with risk of death						0.91

Table 3: Labour market status by health status

	Employed in t	Unemployed in t	Not in the labour market in t
Not ill in $t-1$	0.879	0.028	0.115
Ill in $t-1$	0.812	0.051	0.163
Ill with disability in $t-1$	0.782	0.045	0.196
Ill with risk of death in $t-1$	0.77	0.045	0.21

pooled sample.

Table 4: Health status by labour market status

	Ill in t	Ill with disability in t	Ill with risk of death in t
Employed in $t-1$	0.206	0.027	0.018
Unemployed in $t-1$	0.329	0.037	0.025
Not in the labour market in $t-1$	0.274	0.043	0.03

Finally, persistence and simultaneity seem to characterize health and labour market processes.

In addition, some individual attributes can be observed[5]. Table 5 provides the information pertaining to these variables for the pooled sample and for subsamples defined according the labour market and health status.

[5] Among all these variables, only three (age, number of children, and marital status) vary over time.

Table 5: Socioeconomic characteristics

	Employed	Unemployed	Out of labour market	Ill	Ill with disability	Ill with risk of death	Pooled sample
Men	0.508	0.364	0.095	0.426	0.516	0.481	0.460
Not French*	0.108	0.141	0.195	0.103	0.059	0.08	0.119
Couple	0.705	0.618	0.808	0.734	0.712	0.634	0.713
Number of children	1.257	1.379	2.020	1.613	1.609	1.561	1.350
No grade	0.068	0.134	0.190	0.089	0.101	0.092	0.084
High School grade	0.537	0.543	0.518	0.536	0.555	0.511	0.534
College grade	0.161	0.162	0.141	0.167	0.175	0.181	0.158
Undergraduate studies	0.095	0.068	0.073	0.083	0.083	0.076	0.092
Graduate studies	0.140	0.093	0.077	0.126	0.087	0.14	0.132
Number of obs.	220,812	8,335	31,817	54,989	7,257	4,830	255,206

*: Refers to the individual's nationality.

According to these descriptive statistics, persons who do not participate to the labour market in a given year have certain specific characteristics. As expected, female, less educated people, and those with children are more likely to be out of the labour market. Conversely, among the employed, we count more men and people with academic degrees. Table 5 also shows that female, French people and those with academic degrees report more numerous illness periods. These statistics do not necessarily mean that respondents suffer poorer health; they might just be more concerned about their health and thus declare more illnesses.

Finally, these descriptive statistics argue for taking simultaneity and persistence effects into account to obtain a robust analysis of causality links between health and employment status. We present an econometric framework to fulfill that goal.

2 Econometric framework

2.1 Testing causality: general approach

We first define two dependent variables: health condition ($h = 1$ if an illness is declared, $h = 0$ otherwise) and job status ($w = 1$ if employed, long or short time periods, $w = 0$ otherwise). From the SIP data set, we can observe h and w for each individual i and each year t. Thus we model the interactions between h_{it} and w_{it} while accounting for two points: the path dynamics of each event (and particularly the inertia of each path) and the link between each path. In Figure 1, we present all the links that may exist between the two events over time.

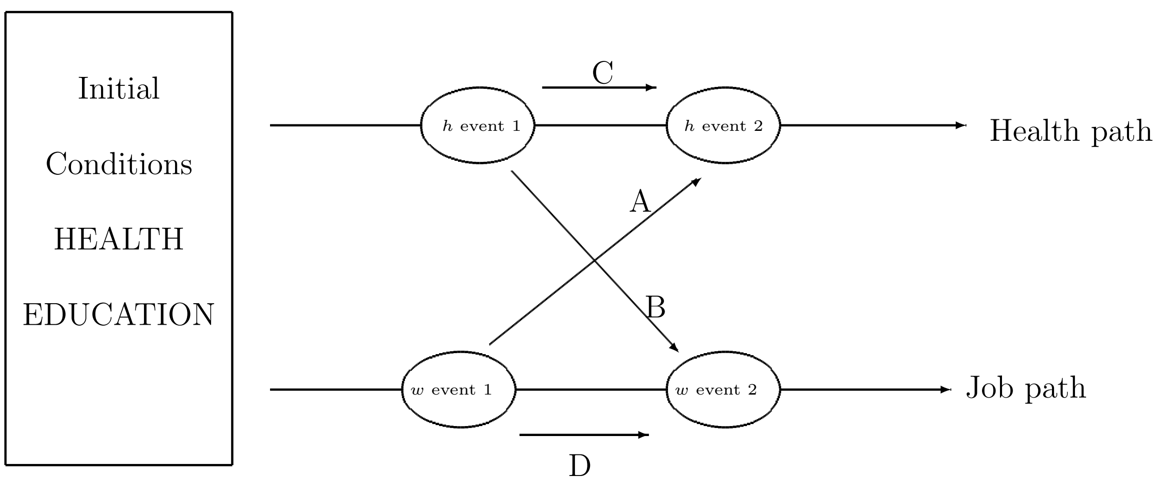

Figure 1: Dynamics of health and job status

In the basic example in Figure 1, four different interactions appear. Links A and B represent the effect of a health outcome (job status) at time $t-1$ on job status (health outcome) at time t. Inertia can also exist (links C and D, such that the probability of being in a good health condition at time $t-1$ influences the health condition at time t). Finally, various sets of control variables may influence h and w.

To identify all these links clearly, we used the causality concept, introduced by Granger (1969). It defines better predictability for a variable Y according to the use of its lag values, the lag value of another variable Z, and some controls X. Granger (1969) distinguishes instantaneous causality, such that Z_t is causing Y_t (if Z_t is included in the model, it improves the predictability of Y_t) from lag causality , in which case the lag values of Z improve the predictability of Y_t. In this section, we rule out instantaneous causality and deal with lag causality for one period.

The one-period Granger causality also can be regarded as conditional independence. Without loss of generality, we present the univariate case for time series. Let Y_t and Z_t denote some dependent variables and X_t denote a set of controls variables. One-period Granger non-causality from Z to Y is the conditional independence of Y_t from Z_{t-1} conditional on X_t and Y_{t-1}. Therefore, Granger non-causality from Z to Y is:

$$f(Y_t|Y_{t-1}, X_t, Z_{t-1}) \quad = \quad f(Y_t|Y_{t-1}, X_t). \tag{1}$$

Note that the same kind of relationship can be written for Granger non-causality from Y to Z. Because Y_t and Z_t are binary outcome variables, we can use latent variables (Y^* and Z^*), with the assumption that Y and Z have a positive outcomes (equal to 1) if their latent variables are positive. The latent variables are defined as follows :
For the left-hand term of Equation 1:

$$\begin{aligned} Y_t^* &= X_t\beta_1 + \delta_{11}Y_{t-1} + \delta_{12}Z_{t-1} + \epsilon_t^1 \\ Z_t^* &= X_t\beta_2 + \delta_{21}Y_{t-1} + \delta_{22}Z_{t-1} + \epsilon_t^2 \end{aligned}$$

For the right-hand term of the Equation 1:

$$\begin{aligned} Y_t^* &= X_t\beta_1 + \delta_{11}Y_{t-1} + \epsilon_t^1 \\ Z_t^* &= X_t\beta_2 + \delta_{21}Z_{t-1} + \epsilon_t^2 \end{aligned}$$

where

$$\begin{pmatrix} \epsilon^1 \\ \epsilon^2 \end{pmatrix} \rightsquigarrow N(0, \Sigma_\epsilon) \ with \ \Sigma_\epsilon \quad = \quad \begin{pmatrix} 1 & \rho_\epsilon \\ \rho_\epsilon & 1 \end{pmatrix}.$$

To fit the joint distribution of Y and Z conditional on X (such that we estimate a bivariate model), we need to analyze four available situations: $(Y = Z = 1)$, $(Y = Z = 0)$, $(Y = 1; Z = 0)$, and $(Y = 0; Z = 1)$. For each of these situation, we have:

$$\begin{aligned}
P\Big(Y_t = 1, Z_t = 1|X_t\Big) &= P\Big(\epsilon_t^1 > -X_t\beta_1 - \delta_{11}Y_{t-1} - \delta_{12}Z_{t-1}, \epsilon_t^2 > -X_t\beta_2 - \delta_{21}Y_{t-1} - \delta_{22}Z_{t-1}\Big) \\
P\Big(Y_t = 0, Z_t = 0|X_t\Big) &= P\Big(\epsilon_t^1 < -X_t\beta_1 - \delta_{11}Y_{t-1} - \delta_{12}Z_{t-1}, \epsilon_t^2 < -X_t\beta_2 - \delta_{21}Y_{t-1} - \delta_{22}Z_{t-1}\Big) \\
P\Big(Y_t = 1, Z_t = 0|X_t\Big) &= P\Big(\epsilon_t^1 > -X_t\beta_1 - \delta_{11}Y_{t-1} - \delta_{12}Z_{t-1}, \epsilon_t^2 < -X_t\beta_2 - \delta_{21}Y_{t-1} - \delta_{22}Z_{t-1}\Big) \\
P\Big(Y_t = 0, Z_t = 1|X_t\Big) &= P\Big(\epsilon_t^1 < -X_t\beta_1 - \delta_{11}Y_{t-1} - \delta_{12}Z_{t-1}, \epsilon_t^2 > -X_t\beta_2 - \delta_{21}Y_{t-1} - \delta_{22}Z_{t-1}\Big).
\end{aligned}$$

By supposing that $q_t^1 = 2Y_t - 1$ and $q_t^2 = 2Z_t - 1$, we can rewrite these probabilities as:

$$P\Big(Y_t, Z_t|X_t\Big) = \Phi_2\Big(q_t^1(X_t\beta_1 + \delta_{11}Y_{t-1} + \delta_{12}Z_{t-1}), q_t^2(X_t\beta_2 + \delta_{21}Y_{t-1} + \delta_{22}Z_{t-1}), q_t^1 q_t^2 \rho_\epsilon\Big)$$

Testing for Granger non-causality in this specification involves testing $\delta_{12} = 0$ for the prediction that Z is not causing Y and testing $\delta_{21} = 0$ for the prediction that Y is not causing Z.

2.2 Testing causality: panel data case

Two main approaches are available for panel data as the SIP survey. The first assumes that the causal effect is not the same for all individuals in the panel (Nair-Reichert and Weinhold, 2001). The specifications for the latent variables are:

$$\begin{aligned}
Y_{it}^* &= X_t\beta_1 + \delta_{11,i}Y_{i,t-1} + \delta_{12,i}Z_{i,t-1} + \eta_i^1 + \zeta_{it}^1, \text{ and} \\
Z_{it}^* &= X_t\beta_2 + \delta_{21,i}Y_{i,t-1} + \delta_{22,i}Z_{i,t-1} + \eta_i^2 + \zeta_{it}^2,
\end{aligned}$$

where $(\eta_i^1, \eta_i^2)'$ denote the individual random effects that are the zero mean and covariance matrix Σ_η, and $(\zeta_{it}^1, \zeta_{it}^2)'$ denote the idiosyncratic shocks that are the zero mean and covariance matrix Σ_ζ, with

$$\Sigma_\eta = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_\eta \\ \sigma_1\sigma_2\rho_\eta & \sigma_2^2 \end{pmatrix} \textit{ and } \Sigma_\zeta = \begin{pmatrix} 1 & \rho_\zeta \\ \rho_\zeta & 1 \end{pmatrix}.$$

In this approach, testing Granger non-causality is equivalent to testing $\delta_{12,i} = 0, i = 1, ..., N$ for the prediction that Z is not causing Y and to testing $\delta_{21,i} = 0, i = 1, ..., N$ for the prediction that Y is not causing Z.

The second approach, which we use herein, acknowledges the causal effects, if they exist, that are the same for all individuals in the panel. With the same notation, the latent variables are:

$$\begin{aligned} Y_{it}^* &= X_t\beta_1 + \delta_{11}Y_{i,t-1} + \delta_{12}Z_{i,t-1} + \eta_i^1 + \zeta_{it}^1 \\ Z_{it}^* &= X_t\beta_2 + \delta_{21}Y_{i,t-1} + \delta_{22}Z_{i,t-1} + \eta_i^2 + \zeta_{it}^2 \end{aligned}$$

Testing for Granger noncausality is equivalent to testing $\delta_{12} = 0$ for the prediction that Z is not causing Y and to testing $\delta_{21} = 0$ for the prediction that Y is not causing Z.

2.3 Dealing with initial conditions

For the first wave of the panel (initial condition), we lack data for the previous state on Y and Z (we have no information on $Y_{i,0}$ and $Z_{i,0}$), so we cannot evaluate $P(Y_{i1}, Z_{i1}|Y_{i,0}, Z_{i,0}, X_i)$. By ignoring it in the individual overall likelihood, we also ignore the data generation process for the first wave of the panel. We suppose the data generating process of the first wave of the panel is exogenous or in equilibrium. These assumptions hold only if the individual random effects are degenerated. Otherwise, the initial conditions (first wave of the panel) can be explained by the individual random effects, whereas ignoring them leads to inconsistent parameter estimates (Heckman, 1981).

The solution proposed by Heckman (1981) for the univariate case and generalized by Alessie et al. (2004) involves estimating a static equation for the first wave of the panel (i.e., we do not introduce lagged dependent variables). In this static equation, the random effects are a linear combination of the random effects in the next wave of the panel, and idiosyncratic error terms may have a different structure from the idiosyncratic error terms in the dynamic equation. Formally, the latent variables for the first wave of the panel are:

$$\begin{aligned} Y_{i1}^* &= X_i^1\gamma_1 + \lambda_{11}\eta_i^1 + \lambda_{12}\eta_i^2 + \epsilon_i^1 \\ Z_{i1}^* &= X_i^2\gamma_2 + \lambda_{21}\eta_i^1 + \lambda_{22}\eta_i^2 + \epsilon_i^2 \end{aligned}$$

where $(\epsilon_i^1, \epsilon_i^2)'$ denote the idiosyncratic shocks, which include the zero mean and covariance matrix Σ_ϵ with $\Sigma_\epsilon = \begin{pmatrix} 1 & \rho_\epsilon \\ \rho_\epsilon & 1 \end{pmatrix}$.

Because η^1 and η^2 are individual random effects on Y and Z, λ_{12} and λ_{21} can be interpreted as the influence of the Y random individual effects (Z random individual effects) on Z (on Y) for the first wave of the panel.

2.4 Estimation methods for health and job paths

Finally, because we want to estimate the dynamic of health (h) and job status (w), we set the following equations for each time period ($t > 1$):

$$
\begin{aligned}
h_{it}^* &= X_t\beta_1 + \delta_{11}h_{i,t-1} + \delta_{12}w_{i,t-1} + \eta_i^1 + \zeta_{it}^1 && (2)\\
w_{it}^* &= X_t\beta_2 + \delta_{21}h_{i,t-1} + \delta_{22}w_{i,t-1} + \eta_i^2 + \zeta_{it}^2 && (3)
\end{aligned}
$$

and for the initial conditions:

$$
\begin{aligned}
h_{i1}^* &= X_i^1\gamma_1 + \lambda_{11}\eta_i^1 + \lambda_{12}\eta_i^2 + \epsilon_i^1 && (4)\\
w_{i1}^* &= X_i^2\gamma_2 + \lambda_{21}\eta_i^1 + \lambda_{22}\eta_i^2 + \epsilon_i^2 && (5)
\end{aligned}
$$

In Equations 2 to 5, many characteristics simultaneously affect health and labour market processes. To achieve the estimations, we also need at least two exclusion restrictions. The variable for the labour market status equation is the national unemployment rate (source: INSEE). The exclusion restriction for health status is set according to the physician per population ratio, also known as the medical density (Delattre and Dormont 2003).

Because the likelihood function has an intractable form (integral function), it is impossible to estimate this likelihood with the usual methods. We therefore deal with numerical integration methods that are numerical approximation method for an integral.

They are two main methods to estimate our likelihood function: the Gauss-Hermite quadrature (GHQ) and the maximum simulated likelihood (MSL). To choose a method, we consider the accuracy and the computing time requirement. For our estimations, we chose the adaptative Gauss-Hermite quadrature proposed by Liu and Pierce (1994)[6].

3 Results

We present econometric results in Tables 6-8. In Table 6, columns (1) and (2) contain the results from bivariate probit regressions for Equations 2 and 3. In columns (1') and (2'), we also provide the univariate probit regressions (with no correlation between the two equations) for these equations. We do the same in Table 7 for the initial conditions (Equations 4 and 5).

The results clearly reveal persistence effects in the health ($\delta_{11} = 3.8243$) and employment ($\delta_{22} = 2.7444$) paths. As Haan and Myck (2009) suggest, we thus confirm the need to study these phenomena dynamically to explain the situation for each individual in terms of her or his health and employment at time t. Evidence for persistence effects also comes from the influence of initial conditions, which depend on various covariates (see Table 7).

We also find the expected, well-known effects of socio economic variables on initial health and employment status. Men are less likely to declare an illness and have better job statuses than women. Elderly people have worse health and job statuses than young people. People without French nationality report less illness and poorer job statuses. Family life also affects health and job conditions: Living as a couple lowers the probability of illness and job stability. The more children in the household, the more illness people experience, and the worse job conditions. Education level creates big differences. More educated people have a lower probability of illness and better job statuses.

The main focus of this paper is on the causality between health and employment status. The bivariate estimates in Table 6 offer strong support. The impact of job status on health is reflected by the coefficient $\delta_{12} = 0.2288$, such that people who have a job at time $t-1$ are more likely to report an illness in the next period t. Two factors could explain these results. First, it could highlight a job quality effect. If being employed involves poor conditions, employment status could readily increase the probability of illness, as argued by Debrand

[6]Moussa and Delattre (2015) provide more details about how to make this choice.

(2001). Unfortunately the SIP survey does not identify longitudinal job quality, so we cannot identify the distinct effect of good or poor working conditions. Second, in France, the health care and insurance system is generous for employed people. For example, they may make regular appointments with their physician, which gives them access to more efficient health monitoring. As a result, they may be more likely to detect and report a disease.

Reporting an illness at time $t-1$ lowers the probability a having a job at time t ($\delta_{21} = -0.1927$). This result illustrates that an illness often makes it difficult to stay or to find a new job (Currie and Madiran, 1999). Our main contribution is thus to conclude that health and employment status do not have a single type of causality but instead show a dual causality effect.

This result derives from taking into account three sources of bias, as described in Section 2: persistence effects, initial conditions, and unobserved heterogeneity. If all these biases were neglected, as in univariate probit models (columns (1') and (2) of Table 6), estimates of the causality effects between health and employment status would be biased. In our case, we would have wrongly concluded that being employed has no effect on health.

Finally, the existence of the causality between health and employment status also appears evidence in Table 7. The coefficients λ_{11} and λ_{22} are both significant, confirming the need to integrate unobserved individual effects η in our model. In addition, the coefficient $\lambda_{12} > 0$ shows that the unobserved individual effect explaining job status (η^2) causes the value of health status at time $t = 1$. The method we have developed here is based on the existence of a correlation between unobservable variables in Equations 2 and 3 and those of Equations 4 and 5. Table 8 gives the values of these correlations. In equations for time $t > 1$ and the initial conditions, correlations between idiosyncratic components are not significant. Therefore, the main unobserved heterogeneity, responsible for the correlation, can be captured with individual-specific effects. In the main equations ($t > 1$), the correlation between individual-specific effects is negative. Therefore, we call for bivariate panel models to avoid any bias in the estimates. We also establish that individual unobserved factors that explain the probability of having a job ($w = 1$) are negatively correlated with individual unobserved factors that explain the probability of declaring an illness ($h = 1$). Among these unobserved factors, individual intrinsic motivation to job and job satisfaction appear to influence individuals' health[7].

Taking advantage of the two other indicators of illness (risk of death and disability, Tables 2 and 3), in Tables 9-11, we provide the estimation results with these variables. Table 9 contains the bivariate results for the indicator of disability (columns 1 and 2) and risk of death indicator (columns $1'$ and $2'$). The impact of health on job status is confirmed by the coefficients $\delta_{21} = -0.4418$ for the disability index and $\delta_{21} = -0.4981$ for the risk of death. The same and even a stronger effect of health status on the probability of having a good quality job emerges, compared with the previous health indicator $\delta_{21} = -0.1927$. When looking at the impact of job status on health, we find no significant effect, in contrast with our prior result. We offer two possible interpretations: First, good jobs provide access to better health coverage and increase the probability of reporting an illness (of any kind). Second, having a job is correlated with poor working conditions. When we control for the severity of health conditions, we find additional support for the first interpretation. Even if people appear induced to report an illness when they have a good job and insurance coverage, the illnesses they report are not particularly severe.

As with the main health indicator (Table 8), we find a significant correlation between individual-specific effects of health and the job status equations (Table 11). The interpretation of the positive sign of these correlations is rather complex. Some unobservable factors that explain the probability of having a job and severe health conditions simultaneously also correlate positively, such as the existence of specific policies designed to protect the job status of disabled persons.

Finally, and contrary to Haan and Myck's (2009; page 1124) claim that "accounting for unobserved heterogeneity reduces the magnitude of the estimated coefficients on the lagged endogenous variables and significantly reduces the persistence of both processes", our estimates clearly show that causality links (A and B, Figure 1) are rather strong, regardless of the illness severity.

[7]Such as mental health (Faragher et al. 2005; Nadinloyi et al., 2013)

Table 6: Estimates of health and job status interactions.

Part A: dynamic equations.

	Bivariate estimations		Univariate estimations	
$Variables$	h : $health$	w : $work$	h : $health$	w : $work$
	(1)	(2)	(1')	(2')
h_{-1}	3.8243^{***} (0.0225)	-0.1927^{***} (0.0138)	4.2513^{***} (0.0154)	-0.2704^{***} (0.0151)
w_{-1}	0.2298^{***} (0.0235)	2.7444^{***} (0.0126)	0.0179 (0.0190)	2.7844^{***} (0.0137)
$Gender$	-0.1571^{***} (0.0169)	0.8095^{***} (0.0137)	-0.0436^{***} (0.0127)	0.5463^{***} (0.0160)
Age	0.0373^{***} (0.0010)	-0.0227^{***} (0.0007)	0.0114^{***} (0.0008)	-0.0089^{***} (0.0007)
$Not\,French^{+}$	-0.0481^{*} (0.0250)	-0.3435^{***} (0.0162)	-0.0217 (0.0191)	-0.2375^{***} (0.0211)
$Couple$	-0.0205 (0.0181)	-0.1211^{***} (0.0137)	-0.0401^{***} (0.0149)	-0.0991^{***} (0.0142)
$Number\,of\,childs$	0.0261^{***} (0.0071)	-0.0758^{***} (0.0052)	0.0168^{***} (0.0057)	-0.0487^{***} (0.0058)
$No\,grade$	0.3808^{***} (0.0372)	-0.9158^{***} (0.0269)	0.1246^{***} (0.0279)	-0.5823^{***} (0.0324)
$College\,grade$	0.3067^{***} (0.0267)	-0.5544^{***} (0.0217)	0.0913^{***} (0.0194)	-0.2787^{***} (0.0239)
$High\,school\,grade$	0.2427^{***} (0.0317)	-0.3639^{***} (0.0253)	0.0811^{***} (0.0232)	-0.1825^{***} (0.0282)
$Undergraduate\,studies$	0.0856^{**} (0.0369)	-0.1470^{***} (0.03)	0.0287 (0.0269)	-0.0925^{***} (0.0326)
Ref : $Graduate\,studies$	-	-	-	-
$Medical\,density$	-0.0009^{***} (0.0003)	-	0.0018^{***} (0.0003)	-
$Unemployment\,rate$	-	0.0714^{***} (0.0022)	-	0.0249^{***} (0.0024)
$Intercept$	-2.6603^{***} (0.0563)	-1.4684^{***} (0.0319)	-2.8887^{***} (0.0464)	-0.3645^{***} (0.0353)

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.

+: Refers to the individual's nationality.

Table 7: Estimates of health and job status interactions.

Part B: the initial conditions.

	Bivariate estimations		Univariate estimations	
Variables	h : *health*	w : *work*	h : *health*	w : *work*
	Initial conditions			
Gender	-0.2425^{***} (0.0616)	0.1555^{***} (0.0319)	-0.1744^{***} (0.0457)	0.144^{***} (0.0317)
Age	-0.0048 (0.0157)	0.0318^{***} (0.0082)	-0.0127 (0.0120)	0.0347^{***} (0.0081)
Not French^{+}	-0.227^{**} (0.1009)	-0.4552^{***} (0.0434)	-0.2062^{***} (0.0771)	-0.452^{***} (0.0432)
Couple	0.0347 (0.08)	0.1579^{***} (0.0468)	0.0427 (0.0607)	0.1526^{***} (0.0466)
Number of child	-0.0213 (0.1354)	-0.5407^{***} (0.0619)	0.0143 (0.0986)	-0.5478^{***} (0.0616)
No grade	0.1925 (0.1666)	-0.592^{***} (0.0863)	0.0625 (0.1277)	-0.5782^{***} (0.0858)
College grade	0.0659 (0.1180)	-0.102 (0.0655)	0.0114 (0.0893)	-0.083 (0.0652)
High school grade	-0.0508 (0.1149)	-0.2165^{***} (0.0622)	-0.0772 (0.0868)	-0.2014^{***} (0.0619)
Undergraduate studies	-0.0836 (0.1157)	-0.0045 (0.0661)	-0.0477 (0.0863)	-0.0001 (0.0659)
Ref : Graduate studies	-	-	-	-
Medical density	0.0005 (0.0008)	-	0.0026^{***} (0.0006)	
Unemployment rate	-	-0.0001 (0.0048)	-	-0.0064 (0.0045)
Ill before prof. life	0.3626^{***} (0.0122)	-0.0018^{***} (0.0047)	0.3465^{***} (0.0090)	-0.0031 (0.0044)
Intercept	-1.5796^{***} (0.3553)	0.429^{**} (0.1864)	-1.8018^{***} (0.2623)	0.5483^{***} (0.1839)
λ_{11}	1.2085^{***} (0.0639)	-		
λ_{12}	0.3969^{***} (0.0557)	-		
λ_{21}	-	0.0324 (0.0296)		
λ_{22}	-	0.1242^{***} (0.0261)		

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.

+: Refers to the individual's nationality.

Table 8: Estimates of health and job status interactions.

Part C: the covariance structure.

Covariance matrix structure	
σ_1	1.3631^{***} (0.0184)
σ_2	1.7269^{***} (0.0161)
ρ_η	-0.8259^{***} (0.0054)
ρ_ζ	0.0275 (0.0174)
ρ_ϵ	0.0227 (0.0460)

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.

Conclusion

This article has examined the relationship between health and labour market paths. Many previous econometric results fail to account for all the links between health and job market status and thus cannot prove any causality. Instead, we propose a new method based on a bivariate dynamic probit model that acknowledges the simultaneity effects between the two phenomena, persistence effects, the role of the initial conditions, and the influence of unobserved heterogeneity. Using a French longitudinal survey we analyze complex interlinks between past and current levels of health and labour market paths. Our results regarding the causality between our two economic outcomes are innovative, due to the novel econometric methodology and the data set we use.

We demonstrate persistence in both processes. Being ill at $t-1$ is a significant determinant of current health status. Simultaneously, we observe the same persistence in labour market paths. We also confirm the impact of initial conditions, which depends an individual attributes and macroeconomic conditions.

Taking advantage of this original econometric modeling, which allows us to distinguish between correlation and causality effects, we highlight some significant causalities between employment and health processes. Being ill at $t-1$ is a significant determinant of current labor market status, and lagged employment has a positive effect on the probability of being ill at time t. In addition, we find an influence of unobserved heterogeneity on the causality effects. These effects are strengthened by the existence of individual-specific effects, which are correlated. When taking these effects into account in our bivariate model, we avoid many biases that univariate modeling cannot avoid.

Finally, our econometric methodology gives us robust estimates of the complex links between health and employment status. Our results therefore argue for a joint definition, in France, of health and employment public policies.

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Table 9: Estimates of health and job status interactions.

Part A: dynamic equations

	Disability index		Risk of death	
$Variables$	h : $disab$	w : $work$	h : $rdeath$	w : $work$
	(1)	(2)	(1')	(2')
h_{-1}	4.0503^{***} (0.0498)	-0.4418^{***} (0.0328)	3.7859^{***} (0.0502)	-0.4981^{***} (0.0366)
w_{-1}	0.0247 (0.0554)	2.737^{***} (0.0127)	-0.0026 (0.0565)	2.7359^{***} (0.0127)
$Gender$	0.0432^{***} (0.0376)	0.8349^{***} (0.0142)	-0.0256 (0.0395)	0.8325^{***} (0.0142)
Age	0.0066^{***} (0.0023)	-0.025^{***} (0.0007)	0.0129^{***} (0.0023)	-0.0249^{***} (0.0007)
$Not\,French^{+}$	-0.1478^{**} (0.0595)	-0.3253^{***} (0.0165)	-0.1146^{*} (0.0618)	-0.3219^{***} (0.0165)
$Couple$	-0.0239 (0.0418)	-0.1207^{***} (0.0138)	-0.1464^{***} (0.0425)	-0.1236^{***} (0.0138)
$Number\,of\,childs$	0.008 (0.0161)	-0.072^{***} (0.0053)	0.0093 (0.0167)	-0.0731^{***} (0.0053)
$No\,grade$	0.0603 (0.0837)	-0.9518^{***} (0.0276)	-0.0412 (0.0837)	-0.961^{***} (0.0276)
$College\,grade$	0.0354 (0.0617)	-0.5797^{***} (0.0224)	-0.0594 (0.0602)	-0.584^{***} (0.0224)
$High\,school\,grade$	0.1002 (0.0722)	-0.3874^{***} (0.026)	-0.0561 (0.0731)	-0.3914^{***} (0.026)
$Undergraduate\,studies$	0.0537 (0.0839)	-0.1516^{***} (0.0312)	-0.0304 (0.0846)	-0.1598^{***} (0.0312)
Ref : $Graduate\,studies$	-	-	-	-
$Medical\,density$	0.0059^{***} (0.0008)	-	0.0057^{***} (0.0009)	-
$Unemployment\,rate$	-	0.0727^{***} (0.0023)	-	0.0726^{***} (0.0023)
$Intercept$	-5.5495^{***} (0.1396)	-1.395^{***} (0.0324)	-5.5168^{***} (0.1539)	-1.3894^{***} (0.0323)

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.

+: Refers to the individual's nationality.

Table 10: Estimates of health and job status interactions.

Part B: the initial conditions

	Disability index		Risk of death	
Variables	h : *disab*	w : *work*	h : *rdeath*	w : *work*
	Initial conditions			
Gender	0.099 (0.1597)	0.16^{***} (0.032)	-0.133 (0.2002)	0.1612^{***} (0.032)
Age	0.059 (0.0418)	0.0312^{***} (0.0082)	0.0274 (0.0529)	0.0311^{***} (0.0082)
Not French^{+}	-0.6606 (0.4388)	-0.4523^{***} (0.0435)	-0.9179 (0.5886)	-0.4547^{***} (0.0436)
Couple	-0.2377 (0.2411)	0.161^{***} (0.0469)	0.1184 (0.2623)	0.1596^{***} (0.047)
Number of child	-0.4369 (0.4986)	-0.5376^{***} (0.0621)	-0.4753 (0.5308)	-0.537^{***} (0.0622)
No grade	0.8817^{**} (0.4354)	-0.5952^{***} (0.0865)	0.3794 (0.5088)	-0.5952^{***} (0.0867)
College grade	0.6666^{**} (0.3344)	-0.1079 (0.0656)	0.1311 (0.3905)	-0.1091^{*} (0.0658)
High school grade	0.2806 (0.3247)	-0.2203^{***} (0.0623)	-0.1777 (0.3767)	-0.2211^{***} (0.0624)
Undergraduate studies	0.4078 (0.3213)	-0.0052 (0.0662)	-0.1988 (0.3912)	-0.0061 (0.0664)
Ref : Graduate studies	-	-	-	-
Medical density	0.0085^{***} (0.0021)	-	0.0111^{***} (0.0028)	
Unemployment rate	-	0.0028 (0.0048)	-	0.002 (0.0048)
Ill before prof. life	0.1403^{***} (0.0137)	-0.0012 (0.0045)	0.1381^{***} (0.0167)	-0.001 (0.0045)
Intercept	-8.3097^{***} (1.0974)	0.3943^{**} (0.1864)	-8.3287^{***} (1.3685)	0.4034^{**} (0.1867)
λ_{11}	1.6651^{***} (0.1381)	-	1.9251^{***} (0.1822)	
λ_{12}	-0.0464 (0.1057)	-	0.0427 (0.127)	
λ_{21}	-	0.0117 (0.032)		-0.0582^{*} (0.0339)
λ_{22}	-	0.1276^{***} (0.0212)		0.1377^{***} (0.021)

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.

+: Refers to the individual's nationality.

Table 11: Estimates of health and job status interactions.

Part C : the covariance structure

	Covariance matrix structure	
	Disability index	Risk of death
σ_1	1.0683^{***} (0.0123)	1.0143^{***} (0.0122)
σ_2	1.701^{***} (0.0163)	1.701^{***} (0.0163)
ρ_η	0.2708^{***} (0.032)	0.2284^{***} (0.0328)
ρ_ζ	0.0468 (0.0482)	0.0175 (0.05)
ρ_ϵ	-0.1515 (0.1161)	0.0175 (0.1522)

The estimated standard deviations for the estimated coefficients are within parenthesis.

***: Significant at the 1% level.

**: Significant at the 5% level.

*: Significant at the 10% level.