THE UNIVERSITY OF MELBOURNE

Melbourne Institute Working Paper Series

Working Paper No. 19/08

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of Applied Economic and Social Research

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ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 978-0-7340-3287-4

September 2008

* The author would like to thank the *Krupp von Bohlen und Halbach Foundation* for financial support, William Greene, John Haisken-DeNew, John Creedy, Lars Siemers, Annika Frohloff, Jan Brenner, Boris Augurzky, Adrian Bruhin, Andrew Jones, Pilar García-Gómez, Martin Gravare, Pedro Rosas Dias, Christoph M. Schmidt, Anthony Scott, Mike Shields, participants of the Health, Econometrics, and Data Group, University of York, the Therapy Hiking Seminar and the Brown Bag Seminar of the RWI Essen, and the MIAESR Workshop, University of Melbourne. All errors are my own.

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Abstract

Empirical evidence from the psychology literature suggests that reactions towards health shocks depend strongly on the personality trait of *locus of control*, which is usually unobservable to the analyst. In this paper, the role of this discrete heterogeneity in shaping the effects of health shocks on labour supply are theoretically modelled by adopting the Grossman (1972) model. Using German longitudinal data, the predictions of the theoretical model are tested with a latent class binary choice model and an alternative identification strategy. A robust result across both specifications for various definitions of locus of control, health shocks and labour market outcomes is that *internals* have a smaller probability of leaving the labour market after experiencing a health shock than *externals*.

1 Introduction

The relationship between socioeconomic status, in particular labour market outcomes, and health is one of the most robust and well documented findings in social science, nevertheless its causal pathways are far from clarified yet. Health shocks, a quasi-natural experiment, have been used as an exogenous variation in health status to successfully identify the causal impact of health on labour market outcomes (Smith, 1999, 2003). Several reasons may explain why individuals experiencing a health shock are more likely to exit the labour market. They might be unable to work or to perform the same duties to the same standard, but also they may have to spend longer hours at general practices or hospitals and, consequently, spend less time at the workplace. If given the opportunity, affected individuals may opt for early retirement, part-time employment, or a prolonged sick-leave, either because they objectively cannot perform daily routines or they perceive their health status to be too weak to work. These dynamics have been strongly confirmed in the empirical literature on the effects of sudden and graduated declines in health on the probability to be unemployed, to be inactive, or to retire (Rice et al., 2007; Hagan et al., 2006; Disney et al., 2006; García-Gómez and López-Nicolás, 2006; Wing Han Au et al., 2005; Riphahn, 1999; Bound et al., 1999).

Even though most studies account for individual differences in the level of labour market outcomes, the empirical literature does not consider the potential of heterogeneous effects of health shocks on labour market outcomes. That is to say, most studies assume that the average response to unanticipated life events in the population results from the same underlying coping behaviour. This is a truly restrictive assumption, as empirical evidence in the psychology literature suggests that individuals differ in their reactions towards sudden changes in life. These differences are referred to as differences in affective style (Davidson, 1992), which are associated with temperament (Kagan et al., 1988) or personality (Gross et al., 1998). The literature also demonstrates that personality differences in responses to sudden health changes can broadly be captured by two types of individuals. Some studies distinguish between optimists and pessimists (Scheier and Carver, 1987), other studies distinguish between individuals who have an internal or an external locus of control (Rotter, 1966, 1982), and some studies speak of left- or right-brainers (Davidson, 1993).

Even though a clear-cut distinction between these concepts is not possible, they nevertheless suggest that assuming slope homogeneity is an inadequate representation of the behaviour in the population, and thus results in a mis-specification of the data generating process in an empirical analysis. The question about assuming the correct data generating process is in so far important, as the homogeneity assumption may lead to biased results (Jedidi et al., 1997; Heagerty and Kurland, 2001) or to a poor fit of the data (McLachlan and Peel, 2000).

In light of these untouched issues, this study assesses discrete heterogeneity in the impact of health shocks on labour market outcomes. To sort out the mechanisms underlying the relationship between the personality trait of locus of control (or optimism/pessimism or right/left brainers) and the labour market response to a health shock, I adopt a two-period simplification of the Grossman (1972) model. The health production function is allowed to differ by individuals, which means that some individuals are more successful in producing healthy days than others despite the same level of inputs, observable characteristics, and rate of health deterioration.

From this theoretical conditional labour supply equation an empirical specification is derived. Using high quality panel data from the German Socio-Economic Panel (GSOEP) and a finite mixture approach, I estimate the probability to become inactive separately for two classes. Mixture models and their variants identify classes of individuals via a finite number of mass points rather than via the full distribution of unobserved individual effects (Haughton, 1997; McLachlan and Peel, 2000; Aitkin and Rubin, 1985). They have been widely applied to capture unobservable heterogeneity in the demand for health care (Deb and Trivedi, 2002, 1997; Deb, 2002) or substance abuse (Van Ours, 2006, 2004), the determinants of happiness (Clark and Etilé, 2006), and the state dependence of health (Halliday, 2008). Mixture models are also attractive as they allow to investigate the determinants of class membership.

As an alternative, I identify the two classes of internal and external locus of control from observable personality data provided for in the GSOEP in wave 2005. On the basis of a personality index constructed from the data, I separate the sample into individuals with internal and external locus of control and interact these indicators with the health shock. The health shock is constructed from both health care utilisation and self-reported health status measures.

The comparative statics of the theoretical model show that in the case of a change in the level of last period's health, the average externally controlled individual is more likely to work less in the second period than the average internally controlled individual. This theoretical result is confirmed in the empirical analysis: across a variety of specifications, the internally controlled individuals have a smaller probability of leaving the labour market after experiencing a health shock than externally controlled individuals, whereas this latter group makes up a smaller fraction of the sample.

The remainder of the paper is structured as follows: Section 2 reviews the empirical literature on the importance of personality traits in determining coping behaviour. Section 3 outlines the theoretical model and Section 4 explains the identification of the latent class model and the alternative estimation strategy. Section 5 describes the data, the construction of the health shock measures, and the construction of the locus of control personality index. Descriptive results are presented in Section 6, while estimation results and the robustness analysis are presented in Section 7. Section 8 concludes.

2 Health, Personality Traits and Coping Behaviour

Personality traits are receiving increasingly attention in the empirical and theoretical economics literature (Borghans et al., 2008). The role of locus of control has been discussed in relationship to job motivation and achievements (Judge and Bono, 2001) and set-point theory in happiness research (Headey, 2008), whereas the role of optimism as one determinant of heterogeneity has been widely acknowledged in the economics literature on happiness. People look at life pessimistically or optimistically, even though there is no difference in their level of well-being, and therefore judge their wellbeing differently (Clark et al., 2005; Groot and Maasen van den Brink, 2007).

A large body of research in health psychology has successfully demonstrated a link between optimism, internal locus of control, and asymmetric brain activity and the coping behaviour of individuals experiencing unanticipated, adverse life-events. In what follows suggests that differences in coping behaviour may be broadly captured by two groups of individuals: independent of the name tags applied, there are some individuals who face little difficulties in coping with adverse life events and some who face large difficulties.

Optimists are considered to adjust better to adverse life events than pessimists. Optimism is usually defined as having general expectations that good things will happen, either now or in the future (Scheier and Carver, 1987)[1]. Optimists differ from pessimists in their stable coping tendencies (Scheier et al., 1986) when confronting stressful events. For instance, women diagnosed and treated for breast cancer appear to respond to a greater degree with fighting spirit, which is associated with greater quality of life and functioning, whereas pessimistic women appear to respond with a greater degree of hopelessness and helplessness (Schou et al., 2005). Also, among patients who were diagnosed and treated for unanticipated illnesses, e.g. cancer or coronary heart disease, optimists returned much faster to vigorous physical activity and were more likely to have a higher quality of life than pessimists. On the other hand pessimists are associated with a higher probability of giving up after a diagnosis or surgery (Rasmussen et al., 2006). In a study on maternal adjustment to pregnancy, it has been shown that optimists are more likely to engage in constructive and problem-focused thinking and to solve daily problems more efficiently. This constructive thinking correlates negatively with later anxiety and positively with later positive states of mind (Park et al., 1997). With respect to coping behaviour towards major life events, optimists show smaller days of sick-leave from work after an adverse event and they return faster to pre-event levels of functioning (Kivimäki et al., 2005), whereas pessimists are more likely to disrupt their social and recreational activities after an illness (Carver et al., 2003).

Similar differences in adjustment to unanticipated events have been reported for individuals who differ in their locus of control[2]. Those with internal locus of control (referred to as *internals* from here onwards) believe they have the ability to significantly alter events while individuals with external locus of control (referred to as *externals* from here onwards) feel that their lives are dominated by the environment and luck (Rotter, 1966, 1982). Individuals facing a spectrum of threatening events appear to adapt better when they perceive control over the consequences of the problem or the recurrence. There are three reasons reported why individuals with an internal locus of control cope better with

[1]Dispositional optimism is measured by the Life Orientation Test (LOT) (or its revised version LOT-R), which consists of 8 coded items, four phrased in a positive way, and four phrased in a negative way plus four filler questions. A typical question of the test is: "In uncertain times, I usually expect the best". Respondents answer each item by indicating the extent of their agreement along a 5-point Likert scale ranging from strongly agree to strongly disagree.

[2]The theory of locus of control was derived from Rotter's Social Learning Theory of 1954, out of which a Locus of Control Scale, the I-E scale, to measure generalised perceptions of individuals had been derived (Rotter, 1966).

stressful events. Perceived control increases predictability as the event unfolds, it may set an upper limit on the perceived adverse consequences, and it undercuts feelings of helplessness (Thompson, 1981).

These adaptational benefits of perceived control have been demonstrated among individuals with breast cancer, rheumatic disease, victims of spinal cord injuries, and mothers of medically fragile infants. Among myocardial infarction survivors, perception of personal control was also linked with a better adherence to recommended behavioural regimes and a higher rate of returning to work following the recuperative period. Internal locus of control has also been associated with knowledge about disease, ability to stop smoking, ability to lose weight, effective use of birth control, getting preventive inoculations, wearing seat belts, and getting regular dental checkups (see Strudler Wallston and Wallston (1978) and Fitzgerald et al. (1993) for an overview of the literature).

Internal locus of control and optimism share certain features to a degree that separating the two is quite difficult. Tennen and Affleck (1987) argue that the problem-focused strategies employed by optimists suggests that they experience a sense of personal control. In fact, Scheier et al. (1986) demonstrated that dispositional optimism positively correlates with problem-focused coping, seeking of social support, and emphasising of the positive aspects of the stressful event. Also, Scheier and Carver (1985) report positive associations between Life Orientation Test (LOT) scores and scores on the Internal-External Locus of Control (I-E) scale.

The behavioural differences towards adverse events between optimists/pessimists and internals/externals may be linked to the literature on asymmetries in brain activities. Most individuals are asymmetric and Davidson (1993) proposed that these asymmetries reflect processes in the brain that moderate trait tendencies of approach and withdrawal from emotional stimuli. Individuals showing more brain-wave activity coming through the left side of the forehead are reported to respond more positive to positive emotions (approach) and individuals showing more brain-activity on the right prefrontal cortex respond more negatively (withdrawal) when exposed to negative emotional stimuli (Wheeler et al., 1993; Coan and Allen, 2003). Individuals with greater relative left-sided activation recover more quickly from an adverse event and show more persistence in pursuing their desired goals (Jackson et al., 2003). Two studies have shown that individuals with highly active right-frontal lobes respond to a stressful event with a more pronounced decline in immune function (Davidson et al., 1999; Rosenkranz et al., 2003). People with a more active left prefrontal region report themselves to be more cheerful, more enthusiastic, more eager and alert, and more engaged in life (Tomarken et al., 1992), which are the main characteristics of positive affect. In return, studies by Warehime and Woodson (1971), Klonowicz (2001) Masters and Wallston (2005) demonstrated a positive association between positive affect and (health) locus of control.

From here onwards I use the concept of locus of control as personality trait of main interest, however, it should be stressed that this measure may capture as well optimism, positive affect, or asymmetry in brain activity.

3 Economic Model

From a theoretical point of view, heterogeneous effects of deteriorating health on labour supply can be modelled in the framework of the Human Capital Model of Health Demand (Grossman, 1972, 1999)[3]. Grossman assumes that the stock of health, defined as illness-free days, is endogenous. Its initial stock may depreciate over time, but an individual is free to invest in health by purchasing medical care or spending time on health improving activities. The total amount of time free of illness in turn determines the total amount of time an individual can spend on producing money earnings and commodities or the utility he or she can derive from. Health is the result of an investment which the individual exerts and its depreciation rate, the latter considered to be a function of age and education.

Grossman's model assumes a homogenous health production function. A doubling of health care utilisation would lead to a doubling of illness-free days in the next time period equally for all agents. Thus, it does not allow for the possibility that individuals with internal or external locus of control could obtain different returns on a health investment, ceteris paribus. The model outlined below acknowledges this important difference.

Let's assume the individual derives direct utility U from consuming a commodity X, leisure L, and health H both in period 1 and 2. The individual maximises an inter-

[3]Grossman's model does not concentrate on the effects of health on lalbour supply, but his model can be re-phrased as a conditional labour supply function in which the amount of hours supplied depends on the endogenous health variable (Currie and Madrian, 1999).

temporal utility function

$$U(X, L, H) = U(X_1, L_1, H_1) + \rho U(X_2, L_2, H_2), \tag{1}$$

in which ρ is the discount factor ($0 \leq \rho \leq 1$), subject to the inter-temporal budget constraint

$$p\Big(X_1 + \frac{X_2}{1+r}\Big) + w\Big(L_1 + \frac{L_2}{1+r}\Big) + kI_1 = y + wH_1 + w\Big(\frac{1}{1+r}\Big)H_2. \tag{2}$$

On the left-hand side of Eq. (2) p, w, r, and k are prices for the consumption good, leisure/work, borrowing capital, and the health investment I_1, respectively. The right-hand side represents full income, in which y is the total amount of non-labour income, H_1 is the initial, fixed health endowment, and H_2 is the health endowment in period 2. Both health endowments are measured as illness-free days, which determine the upper level of days an individual can work. H_2 is defined as a function of the depreciation rate of health δ ($0 \leq \delta \leq 1$), H_1, the investment in health I_1, and a parameter A that proxies the individual's productivity in producing illness-free days:

$$H_2 = AI_1 + (1 - \delta)H_1, \tag{3}$$

The higher A, the higher the return of an investment in health[4]. The crucial assumption in this theoretical model is that A is a positive function of internal locus of control traits (ILC):

$$A = f(ILC), \text{ where } \frac{\partial A}{\partial ILC} > 0. \tag{4}$$

By replacing Eq. (3) into (2), I get:

$$p\Big(X_1 + \frac{X_2}{1+r}\Big) + w\Big(L_1 + \frac{L_2}{1+r}\Big) + kI_1 = y + w\Big(H_1 + \frac{(1-\delta)H_1 + AI_1}{1+r}\Big). \tag{5}$$

[4]Grossman (1972) assumed in his seminal work that education is the productivity shifter. In this paper I disregard the possible shifts due to education, since I investigate the case for individuals of equal educational levels.

The Lagrangean function of the constrained maximisation problem is then:

$$
\begin{aligned}
L &= U(X_1, L_1, H_1) + \rho U(X_2, L_2, AI_1 + (1-\delta)H_1) + \lambda\Big(y + w\Big(H_1 + \frac{(1-\delta)H_1 + AI_1}{1+r}\Big) \\
&- p\Big(X_1 + \frac{X_2}{1+r}\Big) - w\Big(L_1 + \frac{L_2}{1+r}\Big) - kI_1\Big). \qquad (6)
\end{aligned}
$$

Maximising Eq. (6) with respect to X_1, X_2, L_1, L_2, I_1, and λ (marginal utility of wealth) and setting the first derivatives equal to zero yields:

$$
\begin{aligned}
U_{X_1} &= \lambda p, && (7)\\
U_{X_2} &= \frac{\lambda p}{(1+r)\rho}, && (8)\\
U_{L_1} &= \lambda w, && (9)\\
U_{L_2} &= \frac{\lambda w}{(1+r)\rho}, && (10)\\
U_{I_1} &= \frac{1}{\rho}\lambda\big(k - \frac{wA}{1+r}\big), && (11)\\
& y + w\Big(H_1 + \frac{(1-\delta)H_1 + AI_1}{1+r}\Big) \\
&= p\Big(X_1 + \frac{X_2}{1+r}\Big) - w\Big(L_1 + \frac{L_2}{1+r}\Big) - kI_1. && (12)
\end{aligned}
$$

In this notation $U_{(\cdot)}$ refers to the marginal utility of the relevant variable. Assuming for simplicity a log-transformed linear Cobb-Douglas utility function with equal weights of the input factors,

$$U(X, L, H) = \ln X + \ln L + \ln H, \qquad (13)$$

from which the Marshallian demand function for all variables of interest can be derived[5].

$$\lambda = \frac{2+3\rho}{y+(w+\frac{k}{A}(1-\delta))H_1}, \tag{14}$$

$$X_1^* = \frac{1}{p}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big), \tag{15}$$

$$X_2^* = \frac{\rho(1+r)}{p}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big), \tag{16}$$

$$L_1^* = \frac{1}{w}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big), \tag{17}$$

$$L_2^* = \frac{\rho(1+r)}{w}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big), \tag{18}$$

$$I_1^* = \frac{\rho}{(k-\frac{wA}{(1+r)})}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big) - \frac{1-\delta}{A}H_1. \tag{19}$$

Using Eq. (18) and plugging Eq. (19) into Eq. (3) yields the conditional labour supply in period 2 (CLS_2^*):

$$CLS_2^*(A,\delta,H_1,y) = H_2^* - L_2^* = AI_1^* + (1-\delta)H_1 - L_2^*, \tag{20}$$

$$= A\Big[\frac{\rho}{(k-\frac{wA}{(1+r)})}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big) - \frac{1-\delta}{A}H_1\Big] + (1-\delta)H_1$$

$$- \frac{\rho(1+r)}{w}\Big(\frac{y+H_1(w+\frac{k}{A}(1-\delta))}{2+3\rho}\Big), \tag{21}$$

$$= \frac{1}{2+3\rho}\Big[\frac{1}{w}\Big(\frac{2\rho A-1}{1-\rho A}\Big)y + \Big(\frac{2\rho A-1}{1-\rho A}\Big)\big(1+\frac{1-\delta}{A}\big)H_1\Big]. \tag{22}$$

Eq. (22) states that the conditional labour supply is a function of non-labour income y, last period's health H_1, and the changes in health from last to the current period $(1-\delta)H_1$. According to this model, the effects of non-labour income, health, and health changes are a non-linear function of the productivity parameter A and the discount factor ρ.

In what follows illustrates what happens to conditional labour supply if the last period's health changes and how this change depends on the productivity parameter A. Thus, I first differentiate Eq. (22) with respect to H_1 and let, for the sake of simplicity,

[5] The loglinearised utility function parameterises the marginal utilities as: $U_{X_1} = \frac{1}{X_1}, U_{X_2} = \frac{1}{X_2}, U_{L_1} = \frac{1}{L_1}, U_{L_2} = \frac{1}{L_2}$ and $U_{I_1} = \frac{A}{AI_1+(1-\delta)H_1}$.

$\rho = \frac{1}{1+r}$ and $w = k$, so that the price of a health investment equals the wage rate.

$$\begin{aligned}
\frac{\partial CLS_2^*(A,\delta,H_1,y)}{\partial H_1} &= \frac{A\rho}{(k - \frac{wA}{(1+r)})}\frac{w + \frac{k}{A}(1-\delta)}{2+3\rho} - \frac{\rho(1+r)}{w}\frac{w + \frac{k}{A}(1-\delta)}{2+3\rho}, \\
&= \frac{1}{2+3\rho}\Big(\frac{\rho(A+1-\delta)}{1-\rho A} - 1 - \frac{1-\delta}{A}\Big), \qquad (23)\\
&= \frac{1}{2+3\rho}\Big(\frac{1}{A(1-\rho A)}(A+1-\delta)(2\rho A - 1)\Big). \qquad (24)
\end{aligned}$$

Eq. (24) is unambiguously greater than 0 if $1 - \rho A > 0$ and $2\rho A - 1 > 0$. This is given if:

$$\frac{\partial CLS_2^*(A,\delta,H_1,y)}{\partial H_1} > 0 \Longleftrightarrow \frac{1}{2\rho} < A < \frac{1}{\rho}. \qquad (25)$$

Eq. (25) states that the conditional labour supply in period 2 is unambiguously a positive function of increasing health in period 1 if health productivity is bounded between the inverse of the discount factor and its half. What this condition means for the empirical specification is discussed at the end of this chapter.

Taking the cross partial derivative of Eq. (24) w.r.t. A yields:

$$\begin{aligned}
&\frac{\partial^2 CLS_2^*(A,\delta,H_1,y)}{\partial H_1 \partial A} \\
&= B\frac{2\rho A(A+1-\delta) + (2\rho A - 1)(1-\rho A)A - (2\rho A - 1)(A+1-\delta)(-1)\rho A + (1-\rho A)}{[(1-\rho A)A]^2}, \\
&= B\frac{(A+1-\delta)(2\rho(1-\rho A)A + (2\rho A - 1)^2) + (2\rho A - 1)(1-\rho A)A}{[(1-\rho A)A]^2}, \qquad (26)
\end{aligned}$$

where $B = \frac{1}{2+3\rho}$. Since $0 \leq \delta \leq 1$ by assumption and since the denominator is greater than 0, Eq. (26) is unambiguously greater than 0 if $1 - \rho A > 0$ and $2\rho A - 1 > 0$. Again, this is the case, if:

$$\frac{\partial^2 CLS_2^*(A,\delta,H_1,y)}{\partial H_1 \partial A} > 0 \Longleftrightarrow \frac{1}{2\rho} < A < \frac{1}{\rho}. \qquad (27)$$

Given that the condition expressed in Eq. (27) holds, the cross partial derivative in Eq. (26) states that, after an increase in health in period 1, the conditional labour supply in period 2 will be greater the larger the productivity factor A. What this last condition means in practice can best be illustrated with a number example. Since assuming $\rho = \frac{1}{1+r}$ and letting the interest rate at which the individual can borrow to be $r = 0.20$, Eq. (27)

can be re-phrased as:

$$\frac{1+r}{2} < A < 1+r \rightarrow 0.60 < A < 1.20. \tag{28}$$

Internally and externally controlled individuals are considered as two extremes of the same continuum, so the condition says that the most extreme internally controlled individual (A=1.20) can be, at most, double as efficient in producing illness-free days after a depreciation of health than the most extreme externally controlled individual (A=0.60). Empirically, this claim can be tested as the hypothesis that the class of externally controlled are at most double as likely to exit the labour market after having experienced a health shock than the class of internally controlled individuals.

4 Empirical Specification

Eq. (22) provides the basis for the empirical specification of labour supply. To estimate this model, four restrictions are imposed: first, I am only interested in a binary outcome of a positive or zero number of hours worked. The outcome variables are *being unemployed*, *inactive* or *retired*, which are coded to be 1 if the individual provided zero hours of work, and 0 otherwise. Second, the parameter vector of non-labour income is assumed to be homogeneous across individuals. This simplification is chose, because I am empirically exclusively interested in the effects of a health shock on labour supply. Third, I measure only the effects of substantially large health changes and not any health change or the past period's health level. This restriction is imposed since I seek to take advantage of the exogeneity of sudden, unanticipated health changes. Fourth, I do not consider the full distribution of personality types embedded in A, but classify individuals to belong to either group of internal or external locus of control, depending on the value of A. Which threshold value to choose to dichotomise A is a question of the methods used.

Let I_{it}^* be the true, but unobserved utility from becoming inactive:

$$I_{it}^* = X_{it}\beta + \delta(A)HS_{it-1} + Z_{it-1}\phi + \alpha_i + \varepsilon_{it}, \tag{29}$$

where X_{it} is a vector of personal characteristics affecting contemporaneously the probability of leaving the labour market and Z_{it-1} is a vector of household wealth indicators and individual workplace variables lagged by one time period. The variable HS_{it-1} stands for the health shock lagged by one time-period. The parameter vectors β, ϕ and $\delta(A)$ represent the impact of personal characteristics, past period household wealth, past period workplace information, and the past period health shock on the probability to become inactive. From Eq. (26) I deduce that the parameter δ must vary between types of individuals that differ in terms of productivity in health investment (A). It means that δ varies between internally and externally controlled individuals. The error term ε_{it} is assumed to be logistically distributed with a variance normalized to $\frac{\pi}{\sqrt{3}}$ and α_i is an individual-specific error term that picks up all time-invariant characteristics. An individual is observed to be inactive, $I_{it} = 1$, if $I^*_{it} > 0$, and 0 otherwise.

The individual specific effect α_i in Eq. (29) is assumed to be discretely distributed with the conditional density $f(\alpha_j|X, Z, HS)$, where j represents a finite number of mass points. The number of points of support for α_j is $j = 1, 2$. The situation can be viewed as one in which each individual resides in a latent class, which is not revealed to the analyst (Greene, 2007, p. N3-20). The assumption of two latent classes is based on the above cited empirical evidence and my economic hypothesis that all individuals can be broadly classified as internal and externally controlled. The probability density function for Eq. (29) is:

$$f(I_{it}|\Theta) = \pi f_1(I_{it}|\theta_1) + (1-\pi) f_2(I_{it}|\theta_2), \tag{30}$$

where $\Theta = (\theta_1, \theta_2)'$ is the parameter vector of interest which varies between class 1 (θ_1) and class 2 (θ_2), and π is the probability to belong to class 1. From equation (30) one can obtain the component distribution from a two-point finite mixture probability function:

$$f_j(I_i|\theta) = \int_\alpha f(I_i|X, Z, HS, \alpha_j) dG(\alpha). \tag{31}$$

The density *f(.)* is assumed to be logistically distributed to obtain a binomial logit model with two points of support for α_j:

$$\begin{aligned} & Pr(I_{i1}, \ldots, I_{iT_i}|HS_{i0}, \ldots, HS_{iT_i-1}) \\ = & \int_\alpha \Big[\prod_{t=1}^{T_i} Pr(I_{it}|HS_{it-1})\Big] f(\alpha|HS_{it-1}) d\alpha. \end{aligned} \tag{32}$$

The conditional probability π that $\alpha = \alpha_j = (\alpha_1, \alpha_2)$ is modelled as a multinomial logit with a regressor matrix W that may include time-invariant personality traits that proxy locus of control. The coefficients γ_1 and γ_2 need to be chosen such that:

$$\pi_j = Pr(\alpha = \alpha_j) = \frac{\exp(\gamma_j' W)}{\sum_{l=1}^{2} \exp(\gamma_l' W)}, \tag{33}$$

with γ_2 normalized to zero. The final individual likelihood is then:

$$\ln L = \sum_{j=1}^{2} \ln L_j = \sum_{i=1}^{N} \sum_{j=1}^{2} \pi_j \ln \Big[\lambda \Big((2I_{it} - 1)(X_{it}\beta + Z_{it-1}\phi + \delta HS_{it-1} + \alpha_j) \Big) \Big]. \tag{34}$$

To ensure identification, the conditions $1 \geq \pi_1 \geq \pi_2 \geq 0$ and $\sum_{j=1}^{2} \pi_j = 1$ must hold, which can always be achieved by rearrangement after estimation (McLachlan and Basford, 1988). This function can be maximised with the EM algorithm (Dempster et al., 1977), which treats the group membership of each individual as missing data.

Post-estimation, one can calculate the posterior probability that a particular individual i belongs to type c, where $c \in 1, 2$.

$$Pr[i \in c | I_{ij}, W_{ij}] = \frac{\pi_c \Pi_{i=1}^{N} \lambda \Big[d_{ic}((2I_{it} - 1)(X_{it}\beta + Z_{it-1}\phi + \delta HS_{it-1} + \alpha_c) \Big]}{\sum_{j=1}^{2} \pi_j \Pi_{i=1}^{N} \lambda \Big[d_{ij}((2I_{it} - 1)(X_{it}\beta + Z_{it-1}\phi + \delta HS_{it-1} + \alpha_j) \Big]}. \tag{35}$$

The latent class model is estimated with NLOGIT, which uses a general optimisation package rather than the EM algorithm[6]. Greene (2007) suggests that the EM algorithm may not be superior to other algorithms, and therefore NLOGIT uses the faster BFGS algorithm. Starting values for the iterations are obtained by assuming that classes are equally probable (Greene, 2007, N18-10).

A more direct way to distinguish the two latent classes is to use observable information in the data-set on personality traits. In the German Socio-Economic Panel (GSOEP) data on locus of control are available in wave 2005. I construct an index of locus of control out of some of the variables described in Table 6, which is used to assign individuals to groups of internals and externals. The health shock variable is then interacted with the indicator dummy variables for *internals* (I_i) and *externals* (E_i), which take the value 1 if

[6] Another possibility is to use Leisch (2007) FlexMix add-on for R, which provides finite mixtures models for linear regressions, binomial logits, and poisson regressions and relies on the EM algorithm for optimisation.

the individual belongs to either group and 0 otherwise. The adjusted model of inactivity becomes:

$$I_{it}^{*} = \alpha_I I_i + \alpha_E E_i + X_{it}\beta + Z_{it-1}\phi + \delta_I I_i \cdot HS_{it-1} + \delta_E E_i \cdot HS_{it-1} + \varepsilon_{it}. \qquad (36)$$

In Eq. (36) the intercepts and the slope parameters vary across internals (I) and externals (E). As intercept and slope heterogeneity is taken into account by theoretically justified interaction terms, the parameters of the alternative specification can be estimated consistently with Maximum Likelihood within a pooled probit framework.

5 Data

The data necessary to carry out my analysis is taken from the German Socio-Economic Panel (GSOEP) between the years 1995 and 2005. The GSOEP is a longitudinal survey of private households established in West Germany in 1984[7]. My sample includes both men and women aged between 40 and 60 years from both West and East Germany. The age interval is censored from above to avoid the possibility of early retirement and censored from below to concentrate on the onset of age-related illness and disease. An individual is included in the sample if he or she is employed in the year of entry to the panel and has not left the sample before 2005. The latter condition is used, because data on locus of control are available only for wave 2005.

The dependent variable can take three formats: either the individual is inactive, unemployed or retired. All three are tested for the reason that many individuals who intend to retire do so via the road of unemployment or inactivity or vice versa. Unemployment refers to the state of being *registered as unemployed at the Federal Agency of Employment*. The indicator being inactive is constructed from the variable *employment status*, which differentiates between full- and part-time employment and unemployment. Inactivity comprises all individuals in early-retirement, searching for employment, officially registered unemployed, and dropping out of the labour market.

[7]The data used in this paper was extracted from the SOEP Database provided by the DIW Berlin (http://www.diw.de/soep) using the Add-On package PanelWhiz v1.0 (Oct 2006) for Stata(R). PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz generated DO file to retrieve the SOEP data used here and any Panelwhiz Plugins are available upon request. Any data or computational errors in this paper are my own. Haisken-DeNew and Hahn (2006) describe PanelWhiz in detail.

As objective health data is not available over several years in the GSOEP, the health shock indicator is constructed from self-reported health and health care utlilisation data[8]. The measure *satisfaction with health (SWH)* has been widely applied and accepted in the literature as a reliable proxy of objective health (Jones and Schurer, 2007; Frijters et al., 2005). Bound (1991) has shown that subjective measures do not perform necessarily worse than objective measures. SWH is a variable coded from 0 to 10, greater numbers indicating better perceived health. For a sample taken from the GSOEP between 1984 and 1995, Riphahn (1999) has shown that individuals who experience a health shock constructed from *satisfaction with health* are up to three times more likely to experience an objective health limitation. These objective health limitations are, for instance, new health limitations, new chronic disease, average days of sick-leave, sick-leave longer than 6 weeks or the number of hospital visits. One drawback of the self-assessed measure is the large amount of heterogeneity in reporting behaviour. Individuals with the same level of objective health may report their health differently, depending on their perceptions (Juerges, 2007; Lindeboom and Van Doorslaer, 2004; Maurer et al., 2007). Subjective health may also pick up variation in the personality trait of locus of control (Klonowicz, 2001).

Thus, I use two alternative proxies of health to construct the health shock, which are *changes in the number of nights spent at hospital last year* and *the changes in the number of doctor visits in the past three months*. The idea behind these two measures is that individuals with severe health limitations will consult doctoral advice. If a true health limitation exists, the individual will be treated. Especially, nights spent at hospital reflect a health limitation that seems to require surgery, overnight treatment or monitoring.

Changes in health from one time period to another are only interesting if they are deteriorating, i.e. if the difference of units of the health proxy between two time periods is negative. Therefore, a health shock (HS) is coded to be 1 if the changes in health H

[8]An optimal health shock measure would be a purged health measure, which is the predicted value from an estimated model of self-assessed health. The predictors are more objective measures of health as they are based on reports of specific medical conditions. These purged health measures would then be used to estimate the effects of health on the outcome measure (Bound et al., 1999; Disney et al., 2006; Hagan et al., 2006). Also, the legally defined handicap status cannot be used, as it is most likely affected from justification bias. To obtain the handicap status, local authorities do not only use the current health status, but also the current labour market situation of the individual. Individuals could apply for the handicap status in anticipation for early-retirement or drop out of the labour market (Berkel and Börsch-Supan, 2003, p.17).

from last period $t-1$ to the current period t are smaller than the negative value of k:

$$HS_{it} = 1 \text{ if } H_{it} - H_{it-1} < -k, \tag{37}$$

where $k \in \{1, \ldots, 4\}$. H is proxied by health satisfaction, number of nights spent at hospital or number of doctor visits. Eq. (37) is the definition chosen by Riphahn (1999) and García-Gómez and López-Nicolás (2006). Alternatively, the health shock can be defined as:

$$HS_{it} = 1 \text{ if } |H_{it} - H_{it-1}| > k\sigma_H, \tag{38}$$

where σ_H is the standard deviation of the measure of health in the sample and $k \in \{1, \ldots, 3\}$ (Hagan et al., 2006). Independent of the threshold value k chosen, the health shock indicator is lagged by one time period (HS_{it-1}) to ensure that the health shock has taken place before the labour market adjustment.

The explanatory variable of main interest is an indicator of internal and external locus of control. In 2005, respondents of the GSOEP were asked to self-assess their personality traits. The questionnaire was based on the 'Big Five' approach, a psychological concept used to describe and study personality. Fundamental to this approach is the assumption that personality differences between individuals, which are manifested in different ways of behaving and experiencing the world, can be traced back to five basic personality traits: Neuroticism (N), Extraversion (E), Openness to experience (O), Agreeableness (A) and Conscientiousness (C) (Gerlitz and Schupp, 2005). Some of these traits highly correlate with locus of control (and also with optimism and pessimism). In fact, the boundaries between neuroticism, conscientiousness, locus of control, positive affect and optimism are weakly defined, such that concepts seem to have a lot of overlap (Masters and Wallston, 2005; Scheier et al., 1994; Smith et al., 1989).

The second set of the personality questionnaire in the GSOEP captures a sub-set of the 23-item forced choice Locus of Control Scale developed by Rotter (1966). The scale assesses the extent to which one regards one's life chances as being under one's control (internal locus of control) versus being chance-determined, incidental, and unpredictable (external locus of control). Typical statements on Rotter's questionnaire are "Heredity plays the major role in determining one's personality", "Becoming a success is a matter of hard work, luck has little or nothing to do with it", or "What happens to me is my own doing". Another set of the questionnaire targets personality traits of neuroticism (e.g. "tend to worry a lot") or conscientiousness ("do things efficiently"), which influence rational decision-making and effective problem-solving abilities (Shewchuk et al., 1999).

Respondents of the survey have to answer to the question whether a particular personality trait refers to them. They may answer any number between 1 and 7, where 1 stands for *Does not apply* and 7 stands for *Fully applies.* The categories I identified as being related to locus of control are: *Worries a lot* (worry), *Gets nervous easily* (nervous), *Does things effectively and efficiently* (efficient), *How my life goes depends on me* (my life), *What a person achieves in life is above all a question of fate or luck* (luck), *If a person is socially or politically active, he/she can have an effect on social conditions* (change), *One has to work hard in order to succeed* (hardwork), *If I run up against difficulties in life, I often doubt my own abilities* (doubts), *The opportunities that I have in life are determined by the social conditions* (possibilities), *I have little control over the things that happen in my life* (control).

Each indicator is re-coded to be 1 if the self-reported value is strictly greater than the average of the sample for variables that are positively related to internal locus of control, and smaller than the sample average for variables that are negatively related to internal locus of control. For instance, someone who agrees strongly with the statement "To be in control of my own life", is associated with internal locus of control. For this case, the variable is coded to be 1 if the value reported is strictly greater than the sample average. In contrast, someone who strongly disagrees with the statement "What a person achieves in life is above all a question of fate or luck", is also associated with internal locus of control. In this case, the variable would be recorded to equal 1 if the reported value is smaller than the sample average. For the former case we have:

$$PT_{ik}^{internal} = 1 \text{ if } PT_{ik} > \frac{1}{N}\sum_{i}^{N}(PT_{ik}), \tag{39}$$

where PT stands for personal trait, k for a particular personal trait, and N for the total number of individuals in the sample. For the latter case we have:

$$PT_{ik}^{internal} = 1 \text{ if } PT_{ik} < \frac{1}{N}\sum_{i}^{N}(PT_{ik}). \tag{40}$$

An individual is then considered to be an *internal* if:

$$Internal_i = 1 \text{ if } \frac{1}{K}\sum_{k}^{K} PT_{ik}^{internal} > r, \tag{41}$$

and 0 otherwise, where $r \in \{.35, .4, .5\}$ and K is the total number of personality trait variables available. Definition 1 (2, 3) labels an individual as internal if the individual's average value of the personality index is greater than .35 (4, 5), which means that the individual reports for at least 3.5 (4, 5) out of 10 personality trait questions a value above the sample average.

Given that the personality data are available once only at the end of the longitudinal survey, personality is treated as if it is completely stable. Thus, I treat personality traits as if they were measured in the first not the latest wave of the GSOEP, assuming that that life events do not significantly alter the general trait tendencies of an individual[9].

The baseline controls include age-group dummy variables, gender, marital status, education and occupation, the number of persons in the household, living with a partner, employment status of partner, having savings and stocks, living in East Germany, employment history, as well as the net adjusted annual household income. Age-groups run from 41 to 45, 46 to 50, 51 to 55, and 56 to 60. Education and occupation includes individuals who hold the basic or the intermediary qualification from Hauptschule or Realschule, respectively, and who completed an apprenticeship, individuals who finished the university qualifying secondary degree Abitur and who completed at maximum an apprenticeship, and individuals who have obtained a university degree. The household wealth and income variables are lagged by one time period to avoid reverse causality. Time effects are also included, for which the year 2005 serves as the base category. Summary statistics of the control and the dependent variables disaggregated by changes in health satisfaction are provided in Table 7 in the Appendix.

[9]See e.g. Headey (2007) who made the same assumption in a recent paper. Soldz and Vaillant (1999) have shown that personality traits, mainly the three traits, Neuroticism, Extraversion, and Openness, exhibited significant correlations across the 45-year interval, and thus, are relative stable over the life course.

6 Descriptive Analysis

The sample chosen covers approximately 36,000 person-year observations, with an equal proportion of men and women. The variables of main interest are sufficiently large health deteriorations, labour market outcomes and personality traits associated with locus of control.

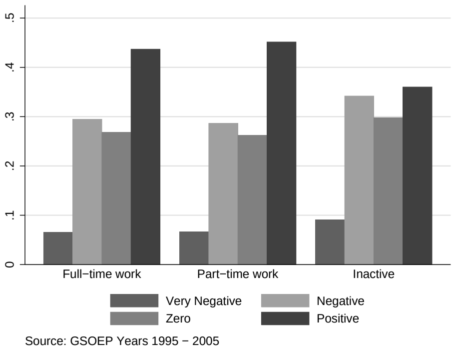
Table 1: Number of individuals inactive after a health shock, by personality

		By personality trait locus of control					
		Definition 1		Definition 2		Definition 3	
k		Int	Ext	Int	Ext	Int	Ext
Health shock = 1 if Health_{it} - Health_{it-1} $<$ - k							
2	HS	202	139	201	140	79	262
3	HS	104	73	103	74	45	132
2	HOSPITAL	191	138	190	139	81	248
3	HOSPITAL	183	128	182	129	77	234
4	HOSPITAL	174	125	173	126	73	226
2	DOCTOR	297	215	295	217	140	372
3	DOCTOR	237	169	236	170	106	300
4	DOCTOR	189	144	189	144	79	254
Health shock = 1 if $\lvert\text{Health}_{it}$ - $\text{Health}_{it-1}\rvert > k \cdot \sigma_H$							
1	HS	202	139	201	140	79	262
2	HS	62	39	61	40	23	78
1	HOSPITAL	140	104	139	105	58	186
2	HOSPITAL	82	69	81	70	36	115
1	DOCTOR	189	144	189	144	79	254
2	DOCTOR	91	72	91	72	33	130

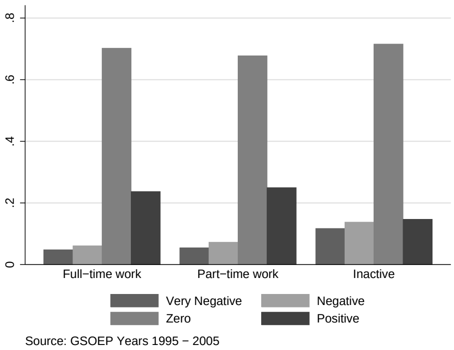
Table 1 reports the number of individuals available in each group of internal and external locus of control who changed from active to being inactive after having experienced a health shock. HS stands for health satisfaction, $HOSPITAL$ stands for number of nights spent at hospital, $DOCTOR$ stands for the number of doctor visits, Int stands for internal locus of control, Ext stands for external locus of control.

Table 1 reports the number of individuals who experienced a health shock in period $t-1$ and who become inactive in period t for various definitions of a health shock and internal locus of control. In general, the number of individuals for each definition of a health shock and internal locus of control exceeds 60. Critical numbers are obtained for health shocks constructed from health satisfaction (HS), when the change is 3 or more units or if the change is greater than 2 standard deviations from the sample average and if the third definition of internal locus of control is used (personality index is greater than 0.5). A similar caveat is in order when using the third definition of locus of control for the changes in health greater than 2 standard deviations for health shocks constructed from nights spent at hospital (HOSPITAL) or doctor visits (DOCTOR). In these cases numbers are in the magnitude of 23 and 33, respectively, for individuals with internal locus of control.

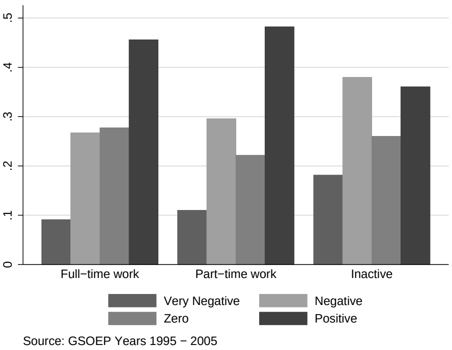
Fig. 1 illustrates for the three proxies of health that contemporaneous labour market



(a) Health satisfaction



(b) Hosiptal visits

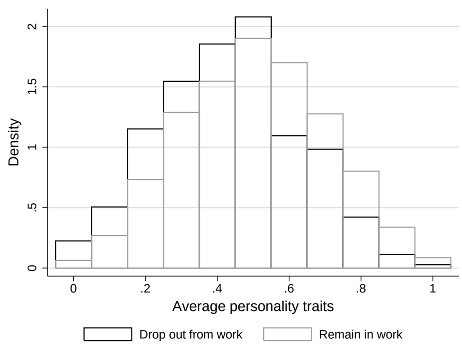


(c) Doctor visits

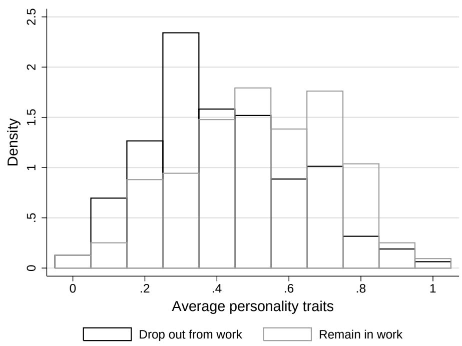
Figure 1: Distribution of health changes by employment status

status depends on the dynamics in health. Positive changes are associated with a smaller proportion of inactivity, whereas very negative changes in health ($HS_{it} = 1$ if $\Delta H_{it} < -2$) are associated with a larger proportion of inactivity in the sample.

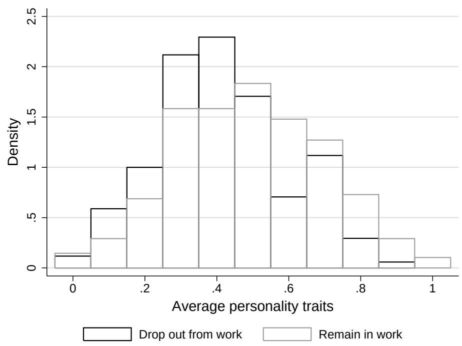
Fig. 2 displays the distribution of the personality index of all individuals who experienced a health shock between period $t-1$ and t separately for those who become inactive and those who remain working in period t. For all three measures of health status one observes that the personality distribution reverses around values of 0.4 to 0.5. A larger proportion of individuals who remained active after a health shock have a personality index of values greater than 0.5 than those who stopped working. Very similar results are obtained for all other proxies of labour market status (results are provided upon request) suggesting some systematic behavioural differences for values on the personality index below or above .4 to .6.



(a) Health satisfaction



(b) Nights spent at Hospital



(c) Doctor visits

Figure 2: Personality index for individuals experiencing a health shock

Table 2 displays the mean differences in self-reported personality traits for those individuals who experienced a past health shock (defined as deterioration in health satisfaction greater than 2 units) and their labour market reaction in terms of whether they retire, become inactive or unemployed. Mean differences in personality traits are considered to be relevant if they are statistically significant at the 5 % level (indicated by the bold font). This is the case for the indicators *worry*, *nervous*, *efficient*, *stress*, *my life*, *luck*, *change*, *decision, doubts*, *possibilities*, and *control*. These are mainly those variables considered in the empirical literature to identify reflections of locus of control. Summary statistics of all control variables are provided in Table 7 in the Appendix.

7 Results

Results are reported only for the effects of a health shock on labour market outcomes. Full results are provided upon request, but estimated coefficients of the control variables yield the expected signs and statistical significance. For instance, there is an age and socioeconomic gradient in the probability of inactivity and the partner's activity status is one of the best predictors of the individual's activity status. Past non-labour income is negatively related to the probability of leaving the labour market. Females, East Germans, and immigrants are more likely to leave the labour market, as is someone who did not work in a company before. Overall, the model explains about 30 % of the variation in employment status with the variation of all included regressors.

7.1 Latent Class Model

Table 3 reports both coefficients and marginal effects of a health shock obtained from a latent class model (LCM), which identifies two latent classes, and a binary logit model (LOGIT), which assumes homogeneity of intercepts and slopes. The results are reported for six different measures of a health shock. Model (1) and (2) derive the health shock from the indicator number of nights spent at a hospital, Model (3) and (4) use health satisfaction, and Model (5) and (6) use number of doctor visits. Two different threshold values are tested. In the odd numbered models a health shock is coded to be 1 if the change from one time period to the next is greater than 1 standard deviation from the sample mean, and 0 otherwise. In the even numbered models a health shock is coded to be 1 if the negative change is greater than 3 (2 for health satisfaction) absolute units on the respective scale, and 0 otherwise.

The following findings are robust across the various model specifications: first, indi-

Table 2: Summary statistics of personality traits by reaction to health shock

		Health shock$_{t-1}$ = 1					
	Full sample	Retire$_t$=0	Retire$_t$=1	Inactive$_t$=0	Inactive$_t$=1	Unemp$_t$=0	Unemp$_t$=1
Communicative	5.5049	5.4821	5.2658	5.4591	5.4633	5.4464	5.5882
	(1.291)	(1.3254)	(1.3933)	(1.3285)	(1.4222)	(1.3378)	(1.4167)
Coarse	2.9886	3.0611	2.8846	3.0458	2.9322	3.0413	2.8824
	(1.6737)	(1.696)	(1.8232)	(1.7054)	(1.7307)	(1.7148)	(1.6505)
Worry	4.8067	5.0665	4.8462	**4.9686**	**5.1875**	**4.9739**	**5.3765**
	(1.6151)	(1.6411)	(1.6986)	(1.6349)	(1.7051)	(1.6428)	(1.6831)
Lazy	2.0603	2.1155	2.2597	2.1363	2.2571	2.1667	2.0706
	(1.4582)	(1.5646)	(1.7045)	(1.571)	(1.6668)	(1.602)	(1.4375)
Sociable	5.0167	5.0689	4.8861	5.0216	5.1638	5.0336	5.1765
	(1.4384)	(1.4596)	(1.5441)	(1.474)	(1.4852)	(1.4831)	(1.4073)
Nervous	3.7048	3.927	4.1392	**3.8892**	**4.1477**	3.9055	4.2262
	(1.7209)	(1.8215)	(1.8996)	(1.7851)	(1.9686)	(1.8018)	(1.9961)
Efficient	5.8869	5.9122	5.7051	**5.8977**	**5.7126**	5.8664	5.8554
	(1.0945)	(1.1117)	(1.3104)	(1.112)	(1.4257)	(1.1752)	(1.1701)
Reserved	4.2127	4.3147	4.3038	4.2843	4.1977	4.2638	4.3529
	(1.5992)	(1.6261)	(1.742)	(1.6167)	(1.7775)	(1.6308)	(1.7975)
Friendly	5.7582	5.7712	5.7468	5.7443	5.774	5.7446	5.8
	(1.1051)	(1.1131)	(1.2554)	(1.1322)	(1.1941)	(1.1543)	(1.0212)
Stress	4.6036	4.4339	4	**4.4394**	**4.2542**	4.421	4.2706
	(1.4772)	(1.5482)	(1.7541)	(1.5447)	(1.6848)	(1.5735)	(1.546)
My life	5.4169	5.4003	5.2911	**5.452**	**5.1695**	**5.4422**	**4.9529**
	(1.362)	(1.4664)	(1.5864)	(1.4204)	(1.6667)	(1.4257)	(1.8316)
Luck	3.5746	**3.6671**	**3.9872**	**3.6096**	**3.9489**	**3.625**	**4.1647**
	(1.6766)	(1.7129)	(1.8126)	(1.7056)	(1.8952)	(1.7222)	(1.9077)
Change	3.6029	3.5321	3.5256	**3.6329**	**3.3295**	3.6002	3.3293
	(1.7047)	(1.7302)	(2.0047)	(1.7402)	(1.8681)	(1.7593)	(1.8193)
Decision	3.1861	3.3117	3.4156	3.2843	3.4686	**3.2916**	**3.6118**
	(1.7245)	(1.8022)	(2.0923)	(1.7542)	(2.1112)	(1.7828)	(2.1827)
Hardwork	6.109	6.1642	6.3038	6.1128	6.3807	6.1353	6.4167
	(1.0677)	(1.1068)	(.8822)	(1.1188)	(.9783)	(1.1133)	(.9079)
Doubts	3.233	3.3571	3.6026	**3.3193**	**3.6875**	**3.351**	**3.7294**
	(1.6862)	(1.73)	(1.854)	(1.7009)	(1.9061)	(1.7328)	(1.8348)
Possibilities	4.5146	4.6813	4.7143	**4.6096**	**5.0571**	**4.6344**	**5.2588**
	(1.5417)	(1.5174)	(1.7981)	(1.5225)	(1.6036)	(1.545)	(1.4488)
Control	2.7454	**2.8992**	**3.1558**	**2.8782**	**3.0229**	**2.8725**	**3.2**
	(1.55)	(1.6396)	(1.8286)	(1.6325)	(1.7713)	(1.6459)	(1.7375)
Abilities	4.9839	5.0398	5.0133	5.0277	5.1214	5.0283	5.2262
	(1.328)	(1.3765)	(1.3506)	(1.3481)	(1.4069)	(1.3629)	(1.302)
Observations	35912	844	92	927	195	1026	95

Table 2 reports the average values of self-reported personality items for the full sample (Column (1)) and for those who experienced a health shock (All other columns). Column (2) and (3) report the average values for those who retired or did not retire after the health shock, Column (4) and (5) report the average values for those who stayed active or those who didn't after the health shock, and Column (6) and (7) report the average values for those who stayed employed or those who didn't after the health shock. All variables are scaled between 1 and 7, where lower values indicate *does not apply* and higher values indicate *fully applies*. Statistical significance of the difference in mean values between the two groups are indicated in bold.

viduals belonging to class 2 face a statistically significant smaller baseline probability of unemployment than individuals in class 1 across all models (1 % significance level). Second, individuals in class 2 react less sensitively to a health shock than individuals in class 1. This difference is approximately 0.20 on a logit scale for a health shock constructed from nights spent at hospital (Model (1) and (2)), 0.22 for health satisfaction (Model (3)), and 0.18 to 0.26 for number of doctor visits. Third, the marginal effect of a health shock obtained from the latent class model, which is the weighted[10] average of the marginal effect of class 1 and class 2, is at least one third smaller than the one obtained from a simple binary logit model. One exception is Model (3) where no differences are obtained. For instance, in Model (1) and (2) the binary logit model predicts that an average individual experiencing a health shock is nearly 6 % more likely to become inactive than someone who didn't, whereas the latent class model predicts less than 4 %. The marginal effects derived from the latent class model is a weighted average of the two marginal effects for class 1 and class 2, which suggests that the individual marginal effects of the two classes delimit the upper and lower bound of an average behavioural reaction towards a health shock.

The determinants of class membership are reported in the lower part of Table 3. An individual in class 1 is more likely to worry a lot (WORRY), to be nervous in difficult situations (NERVOUS), to believe that opportunities in life are shaped by social conditions (POSSIBILITY) and that he or she is not in control of his or her life (CONTROL). A member in class 1 is less likely to believe that his or her life course depends on him- or herself (MYLIFE) and that he or she is efficient in solving problems (EFFICIENT)[11]. These variables are what the reviewed literature would state as differences in internal and external locus of control. Internals are more likely to believe that they can change their own fate and react efficiently in difficult situations, become less nervous, and worry less. Externals are expected to react in the opposite way. For this reason, I suggest to label individuals in class 1 as externally controlled and individuals in class 2 as internally controlled individuals.

According to the prior probabilities, there are approximately 20 % externals and 80

[10]Weights are the posterior probabilities of class membership.

[11]Effects of the variables having doubts (DOUBTS), believing in possibilities to make changes (CHANGE), believe in hardwork to have success (HARDWORK), and that life depends on luck (LUCK) are statistically insignificant. These results are omitted from the table.

% internals in the sample. These results are robust across different definitions of health shocks. According to the Akaike Information Criterion (AIC), the LCM fits the data better than the binary LOGIT model. I also attempted to identify, unsuccessfully, a model with three classes.

7.2 Alternative Method

In this section I report the estimated marginal effects of a health shock on the probability of exiting the labour market from a model using observable personality data to identify heterogeneity in the population. Table 4 constructs the health shock from the number of nights spent at hospital. Estimation results using health satisfaction and number of doctor visits are reported in Table 8 and Table 9 in the Appendix. In Model (1) the health shock is assumed to have a homogeneous effect on the probability of becoming inactive, disregarding the importance of locus of control. In Models (2), (4), and (6) the effect of a health shock is allowed to differ between internally and externally controlled individuals, but both personality types are assumed to face the same base probability of becoming inactive (homogeneous intercept). In Models (3), (5), and (7) both intercept and slope heterogeneity across personality types are modelled.

The estimation results suggest that a similar pattern emerges for all three health measures. First, independent from the personality type (Model (1)), a health shock increases the probability of becoming inactive by 3 to 8 %, whereas the effect is smallest for health satisfaction and greatest for nights spent at hospital.

Since the effect is the greatest for the measure of *nights spent at hospital*, I interpret the estimation results for this shock definition. Distinguishing the effect of a health shock between internals and externals, but assuming equal base-line inactivity risks between the two, yields a marginal effect of a health shock nearly double the size for externals than for internals. For instance, Model (2) in Table 4, in which the health shock is coded as health deterioration greater than 1 standard deviation from the sample mean, reveals that externals are 12 % more likely to exit the labour market after having experienced a health shock (relative to those who haven't), whereas internals are only 6 % more likely. These behavioural differences remain present, though less dominant, when allowing the base-line inactivity probability to differ between internals and externals. Internals are

Table 3: Latent class models for various health shock measures

	Hospital nights		Health satisfaction		Doctor visits	
	$\|\Delta\| > 1\sigma$	$\Delta \leq -3$ units	$\|\Delta\| > 1\sigma$	$\Delta \leq -2$ units	$\|\Delta\| > 1\sigma$	$\Delta \leq -3$ units
	(1)	(2)	(3)	(4)	(5)	(6)
LOGIT						
Constant	2.013	2.021	2.019	2.040	2.015	2.009
	(.407)***	(.407)***	(.406)***	(.4060)***	(.407)***	(.407)***
Health shock	.8297	.6213	.2558	.2492	.6630	.5894
	(.095)***	(.083)***	(.077)***	(.110)**	(.078)***	(.070)***
LCM						
Class 1						
Constant	2.066	2.067	2.072	2.087	2.075	2.059
	(.090)***	(.090)***	(.090)***	.090)***	(.090)***	(.090)***
Health Shock	1.203	1.035	.7280	.7655	1.019	.9476
	(.121)***	(.113)***	(.103)***	(.124)***	(.107)***	(.099)***
Class 2						
Constant	-.7771	-.7848	-.7730	-.7794	-.7709	-.7664
	(.082)***	(.082)***	(.081)***	(.081)***	(.081)***	(.081)***
Health Shock	1.003	.8380	.5091	.7737	.8376	.6886
	(.112)***	(.105)***	(.100)***	(.113)***	(.102)***	(.097)***
Marginal effect of a health shock						
LCM	.0373	.0314	.0200	.0278	.0312	.0266
	(.004)***	(.004)***	(.003)***	(.004)***	(.003)***	(.003)***
LOGIT	.0591	.0451	.0210	.0217	.0500	.0440
	(.006)***	(.005)***	(.005)***	(.007)***	(.005)***	(.004)***
Effect of personality traits on probability to belong to class 1						
WORRY	.2133	.2118	.2110	.2147	.2082	.2076
	(.035)***	(.035)***	(.035)***	(.035)***	(.035)***	(.0347)***
NERVOUS	.0894	.0898	.0945	.0931	.0852	.0858
	(.029)***	(.029)***	(.030)***	(.029)***	(.029)***	(.029)***
EFFICIENT	-.2122	-.2111	-.2100	-.2131	-.2065	-.2070
	(.043)***	(.043)***	(.043)***	(.043)***	(.043)***	(.043)***
MY LIFE	-.1084	-.1070	-.1097	-.1086	-.1046	-.1048
	(.035)**	(.035)***	(.035)***	(.035)***	(.035)***	(.035)***
POSSIBILITY	.0839	.0847	.0783	.0785	.0823	.0803
	(.034)**	(.034)**	(.034)**	(.034)**	(.034)**	(.034)**
DOUBTS	-.0519	-.0520	-.0501	-.0519	-.0441	-.0452
	(.0315)*	(.031)*	(.031)	(.031)*	(.032)	(.031)
CONTROL	.1018	.1013	.1015	.1020	.0963	.0967
	(.032)***	(.032)***	(.032)***	(.032)***	(.032)***	(.032)***
Prior Probabilities to belong to:						
Class 1	.19880	.19858	.19579	.19853	.20037	.20050
Class 2	.80120	.80142	.80421	.80147	.79963	.79950
Akaike Information Criterion						
LCM	.50308	.50378	.50582	.50587	.50345	.50369
LOGIT	.52121	.52184	.52325	.52345	.52132	.52131

Table 3 reports coefficients and marginal effects of a health shock (t-1), on the probability of current period inactivity from a latent class logit (LCM) and a binary logit (LOGIT) model. Inactivity is defined for all individuals who are registered unemployed, retired or currently searching for a new employment. All models control for age, gender, immigrants status, living in East Germany, last period household wealth and income proxied by having savings, having stocks and the log of household income, last period employment characteristics, living with a partner, partner's employment status, human capital indicators, and year dummies. Model (1) and (2) defines the health shock via the number of nights spent at hospital, Model (3) and (4) via health satisfaction, and Model (5) and (6) via the number of doctor visits. The odd numbered models construct the health shock to be 1 if the change in the measure from one time period to another was greater than the standard deviation from the sample mean, and the even numbered models define the health shock to be 1 if the change is at least 3 units on the scale of the respective measure. AIC means Akaike Information Criteria. Robust standard errors are reported in parentheses. * 10 %, ** 5 %, *** 1 % significance level.

generally less likely to become inactive than externals between 2 to 4 % points across all model specifications.

Similar differentiated effects are obtained for the number of doctor visits and health satisfaction when the health shock is measured in terms of standard deviation from the mean. There are only two cases in which the effect of a health shock hardly differs between internals and externals; one is for the number of doctor visits when using the third definition of locus of control (Table 9, Model (7)) and another when using unit change difference to construct a health shock from health satisfaction (Table 8, lower part).

In the case of health satisfaction it may well be that personality types are reflected in the response behaviour of self-assessed health. Internals may report their average health satisfaction to be higher than externals given the same level of objective health. This may also be the reason why differential effects are the smallest between types for this health proxy.

For all models I tested for the joint null hypothesis that the base-line risk of inactivity and the effects of a health shock do not differ between internals and externals. This hypothesis is rejected for all models at the 1 % significance level (for one model at 5 %). Respective F-statistics and their p-values are reported at the bottom of each table.

These empirical results are in line with my theoretical requirement that internals are at most double as effective in producing (perceived) illness-free days after a health deterioration than externals. In almost all of the tested models externals are at maximum 50 to 70 % more likely to drop out of the labour market after experiencing a health shock than internals.

7.3 Comparison of Results

Whether the estimated effects of the alternative method are are comparable to those obtained from the latent class model, is shown in Table 5. The similarities in coefficients between models are illustrated for the effect of a health shock defined as the changes in nights spent at hospital greater than 1 standard deviation from the sample mean and internal locus of control is defined with definition 1.

The intercept and slope coefficients in the latent class model are greater by approxi-

Table 4: Health shock constructed from number of nights spent at hospital

	NO Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog
				Locus of control			
		Definition 1		Definition 2		Definition 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lvert\Delta_{HN,t-1}\rvert > 1\sigma_{HN}$							
Pooled binary logit							
Health shock	0.078						
	(0.012)***						
Separation between internals and externals							
Health shock internals		0.057	0.066	0.057	0.066	0.040	0.061
		(0.014)***	(0.014)***	(0.014)***	(0.014)***	(0.018)**	(0.020)***
Health shock externals		0.119	0.098	0.119	0.097	0.098	0.083
		(0.025)***	(0.022)***	(0.025)***	(0.022)***	(0.016)***	(0.015)***
Internals			-0.019		-0.019		-0.024
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	67.18	5.12	12.81	5.12	13.31	5.24	22.05
P-Value	0.00	0.02	0.00	0.02	0.00	0.02	0.00
$\Delta_{HN,t-1} \leq -3$							
Pooled binary logit							
Health shock	0.052						
	(0.009)***						
Separation between internals and externals							
Health shock internals		0.031	0.038	0.032	0.039	0.018	0.036
		(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.014)	(0.015)**
Health shock externals		0.094	0.075	0.093	0.074	0.069	0.057
		(0.019)***	(0.017)***	(0.019)***	(0.017)***	(0.012)***	(0.011)***
Internals			-0.018		-0.018		-0.023
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	48.69	9.63	14.85	9.22	15.02	7.23	22.21
P-Value	0.00	0.00	0.00	0.00	0.00	0.01	0.00

Table 4 reports the marginal effects of a health shock on the probability of current period inactivity. The health shock is defined by either 1 standard deviation of health deterioration from the sample average of nights spent at hospitals ($\lvert\Delta_{HN,t-1}\rvert > 1\sigma_{HN}$) or by health deteriorations of at least 3 units of nights spent at hospital from one to another period ($\Delta_{HN,t-1} \leq -3$). Inactivity is defined as all individuals who are either registered unemployed, retired or currently searching for new employment. All models control for age, gender, immigrants status, living in East Germany, last period household wealth and income proxied by owing stocks, having savings, and the log of household income, last period employment characteristics, living with a partner, partner's employment status, human capital indicators, and year dummies. Model (1) assumes a homogeneous effect of a health shock across personality types (No Heterog). Model (2) allows the effect to differ between internals and externals, but assumes that both face the same unemployment probability in the absence of the shock (Intercept homog). Model (3) assumes that the overall inactivity probabilities differ between internals and externals (Full heterog). F-Statistic and P-value report test whether the marginal effects of the health shocks differ between internals and externals in Model (2), (3), and (4): $H_0 : \delta_o = \delta_p$ and in Model (3), (5), and (7): $H_0 : \delta_o = \delta_p$ & $\alpha_o = \alpha_p$. Robust standard errors are reported in parentheses. * 10 %, ** 5 %, *** 1 % significance level.

mately 0.250 points than in the alternative LOGIT specification. However, the difference in slope coefficients between internals and externals is very similar across the two models. For instance, in both models externals have a coefficient for the health shock 0.2 points greater than the one for internals. Also, the LCM suggests that 80 % of the sample belong to class 2, the class which I suggest to label internal locus of control. Using the first definition of internals (reporting at least 3.5 out of 10 items related to internal locus of control beyond the sample average) yields a sample of 70 % of internals.

Due to these similarities, it is tempting to propose that, for my particular sample and research question, a latent class model picks up and models the type of unobserved discrete heterogeneity, which is actually present in the data.

Table 5: Comparison latent class and logit models

	LCM	LOGIT	LCM	LOGIT	LCM	LOGIT
	Hospital nights		Health Satisfaction		Doctor visits	
	(1)	(2)	(3)	(4)	(5)	(6)
Class 1 - Externals						
Constant	2.066	1.744	2.072	1.767	2.075	1.760
	(.090)***	(0.568)***	(.090)***	(0.568)***	(.090)***	(0.568)***
Health shock	1.203	0.904	.7280	0.342	1.019	0.701
	(.121)***	(0.155)***	(.103)***	(0.124)***	(.107)***	(0.118)***
Prior probabilities LCM	0.198		0.195		0.201	
Sample proportion LOGIT		30.85		30.85		30.85
Class 2 - Internals						
Constant	-.7771	-0.240	-.7730	-0.248	-.7709	-0.238
	(.082)***	(0.072)***	(.081)***	(0.073)***	(.081)***	(0.073)***
Health shock	1.003	0.676	.5091	0.254	.8376	0.608
	(.112)***	(0.115)***	(.100)***	(0.087)***	(.102)***	(0.093)***
Prior probabilities LCM	0.8012		0.804		0.799	
Sample proportion LOGIT		69.15		69.15		69.15

Table 5 reports the coefficients of a latent class model (LCM) identifying two classes and compares them to the results obtained from a binary logit model (LOGIT) that identifies types with observable data. Internals are defined as those individuals whose personality index is greater than 0.35 and the health shock is defined as a change greater than 1 standard deviation from the sample mean. Model (1) and (2) define the health shock via the number of hospital visits, Model (3) and (4) construct the health shock from changes in health satisfaction, and Model (5) and (6) construct the health shock from the number of doctor visits. Robust standard errors are reported in parentheses. * 10 %, ** 5 %, *** 1 % significance level.

In a robustness check, I have repeated the same analysis for alternative measures of labour market status, i.e. retirement, unemployment, and an alternative measure of inactivity (less than 15 hours of work per week). In their core, results are similar, except for retirement, for which differences between internals and externals are rather small. These results are provided upon request.

8 Conclusion

This paper addresses theoretically and empirically the challenge of modelling discrete heterogeneity in the labour market response to sudden, unanticipated health changes. By adopting a two-period generalisation of the Grossman (1972) model, I show that individuals who are more efficient in producing health are supplying more hours of work after a change in health than those who are less efficient. These differences in productivity are interpreted as differences in the personality trait locus of control. Attitudes towards goal achievement and control of life events are observed to significantly determine coping behaviour, and thus labour market adjustment to health shocks. Empirical findings of the theory of coping behaviour and the biological foundations of asymmetric brain activity additionally suggest that heterogeneity in coping behaviour can be sufficiently captured by two groups that represent internally and externally controlled individuals, rather than modelling heterogeneity across a continuum of types. This observation substantially simplifies the methods available for modelling heterogeneity.

Empirically, I test the hypothesis that externals are more likely to exit the labour market in the event of an adverse health shock than internals. Using 11 waves of the German Socio-Economic Panel (GSOEP) and a unique set of personality variables available in the year 2005, I apply a latent class model and an alternative identification strategy to test my hypothesis. The latent class model separates the sample into two classes on the basis of time-invariant unobserved heterogeneity clustering around two mass points. Alternatively, unobserved heterogeneity is controlled for by assigning individuals directly to a group of internals and externals on the basis of a personality index constructed from observable data. Even though using a noisy measure of health shocks, constructed from health care utilisation variables and health satisfaction, I find robust evidence for my hypothesis in the data.

For both estimation strategies, for various definitions of locus of control, health shocks and labour market outcomes, my results suggest that internals have a smaller probability of leaving the labour market of 30 to 100 % after experiencing a health shock than externals. A binary choice model ignoring the difference in classes over-estimates the average effect of a health shock by about a third. Both identification strategies of the two classes yield similar results.

Between 70 to 80 % of the sample have a relatively small probability to leave the labour market after experiencing a severe deterioration of health. It is a minority of 20 to 30 % of the sample who are at high risk to drop out. Individuals in this sample are associated with self-reported traits of worrying a lot, lacking confidence in their own abilities and being less efficient to tackle unexpected events. Having said this, one needs to be careful about the labels attached to the groups. The psychology literature does not strictly distinguish between traits such as locus of control and optimism/pessimism or even other personality traits such as neuroticism and conscientiousness. This study only provides evidence that certain personality traits, which are associated with locus of control, optimism, and positive affect are crucial in determining coping behaviour.

There are two important implications of the finding, that a small proportion in the sample faces a relative high risk of dropping out of the labour market after experiencing a health shock. On the one hand, estimated marginal effects of a health shock from other studies with a similar research question and study design most likely under-estimate the risk of becoming unemployed for some part of the sample and over-estimate the risk for a major part of the population. For instance Riphahn (1999), the study closest linked to my study design that also used the GSOEP, finds coefficients on the log odds ratio that are larger than the ones I obtained in the pool model without controlling for discrete heterogeneity. Hagan et al. (2006) look at hazard rates of the effects of health shocks on the retirement decision using the European Community Household Panel (ECHP). In a pooled sample and using self-assessed health they identify an increase of the probability of retirement in due course of a health shock of nearly 50 %. García-Gómez and López-Nicolás (2006) use difference-in-difference and matching techniques to find a significant effect running from health to the probability of employment, also using the ECHP. They estimate an average treatment effect of the treated in the magnitude of 3.5 to 5 %, a result similar to the marginal effect obtained for internals in my sample. In all three studies, had they differentiated between internals and externals, the risk of dropping out of the labour market would be even greater for externals than predicted in my study.

On the other hand, my results raise the question whether there is an appropriate balance in the division of labour between the health care and the safety net institutions in supporting high risk individuals. If it is true that a small group of individuals faces a high risk to drop out of the labour market in general and after experiencing an unanticipated health shock, then it is the health care system that should help affected individuals to overcome these shocks (Deaton, 2002), rather than waiting until the safety net catches those who drop out of the labour market in the form of social security or unemployment benefits. This claim is even more pressing, if we consider the large growth rates of depression, a health impairment associated with negative affect and loss of control over one's own life, in Western societies (Copeland et al., 2004).

Appendix

Variables reported in Table 6 are taken from the GSOEP Questionnaire 2005, section "What personality do you have". This section contains three sub-sections, namely "I see myself as someone who ...", "To what degree do the following statements apply to you personally?", and "The following statements apply to different attitudes towards life and the future. To what degree do you personally agree with the following statements?". The questionnaire informs the respondent with the following information:

> "You will probably find that some apply to you perfectly and that some do not apply to you at all. With others, you may be somewhere in between. Please answer according to the following scale: 1 means 'does not apply to me at all', 7 means 'applies to me perfectly'. With values between 1 and 7, you can express where you lie between these two extremes."

Table 6: Description personality variables

Please answer between 1 (does not apply) to 7 (does apply)

Variable	Question
	I see myself as someone who ...
Thorough	"does a thorough job"
Communic	"is communicative, talkative"
Coarse	"is sometimes somewhat rude to others"
Original	"is original, comes up with new ideas"
Worry	"worries a lot"
Forgive	"has a forgiving nature"
Lazy	"tends to be lazy"
Sociable	"is outgoing, sociable"
Nervous	"gets nervous easily"
Efficient	"does things effectively and efficiently"
Reserved	"is reserved"
Friendly	"is considerate and kind to other"
Imagine	"has an active imagination"
Stress	"is relaxed, handles stress well"
	The following statements apply to different attitudes towards life and the future. To what degree to you personally agree with the following statements?
My life	"How my life goes depends on me"
Deserve	"Compared to other people, I have not achieved what I deserve"
Luck	"What a person achieves in life is above all a question of fate or luck"
Change	"If a person is socially or politically active, he/she can have an effect on social conditions"
Decision	"I frequently have the experience that other people have a controlling influence over my life"
Hardwork	"One has to work hard in order to succeed"
Doubts	"If I run up against difficulties in life, I often doubt my own abilities"
Possib	"The opportunities that I have in life are determined by the social conditions"
Abilities	"Inborn abilities are more important than any efforts one can make"
Control	"I have little control over the things that happen in my life"

Table 7: Descriptive statistics by changes in health

	All	ΔHS < 0	ΔHS < -1	ΔHS < -2	ΔHS < -3	ΔHS = 0
Labour market status						
Retired	.0727	.0863	.0935	.0983	.1124	.0718
	(.2597)	(.2809)	(.2912)	(.2979)	(.3162)	(.2581)
Inactive	.1249	.157	.1701	.1738	.2038	.1194
	(.3306)	(.3638)	(.3758)	(.3791)	(.4032)	(.3243)
Inactive & work < 15)	.1471	.1865	.2007	.2032	.2283	.1406
	(.3542)	(.3895)	(.4006)	(.4026)	(.4201)	(.3476)
Unemployed	.0566	.0778	.0868	.0847	.1059	.0524
	(.2312)	(.2678)	(.2816)	(.2786)	(.3079)	(.2227)
Household income & wealth						
Monthly income	3360.521	3166.517	3134.281	3155.431	3075.717	3395.729
	(2410.115)	(2112.089)	(2145.618)	(2332.81)	(1923.881)	(2498.663)
Savings	.7005	.6641	.6475	.6308	.6335	.7085
	(.4581)	(.4723)	(.4778)	(.4828)	(.4823)	(.4545)
Monthly savings	361.3261	302.0986	290.3713	270.189	267.6389	372.1248
	(907.077)	(517.3641)	(547.4904)	(452.5567)	(428.8345)	(958.0172)
Income interest	526.9889	442.8127	537.1275	776.6517	250.2727	566.4144
	(10118.51)	(8785.548)	(12372.07)	(17536.86)	(1848.385)	(10888.34)
Income renting out	2614.892	2366.899	2484.976	2402.823	2764.889	2677.348
	(14039.08)	(11838.03)	(14266.43)	(10325.33)	(10809.8)	(14390.12)
Stocks	.2659	.2386	.2293	.2216	.2126	.2727
	(.4418)	(.4263)	(.4205)	(.4155)	(.4096)	(.4454)
Account	.7827	.7582	.7427	.7348	.7203	.7877
	(.4124)	(.4282)	(.4372)	(.4416)	(.4493)	(.4089)
Human capital stock						
9 to 10 yrs school	.0638	.0777	.0854	.0963	.1019	.0618
	(.2444)	(.2677)	(.2796)	(.2951)	(.3028)	(.2408)
10 yrs school + training	.4589	.4891	.484	.4661	.4736	.4514
	(.4983)	(.4999)	(.4998)	(.4991)	(.4998)	(.4976)
12 to 13 yrs school + training	.1555	.1538	.1518	.1595	.1585	.1549
	(.3624)	(.3608)	(.3589)	(.3663)	(.3655)	(.3618)
University degree	.2814	.2495	.2447	.2451	.2358	.2862
	(.4497)	(.4328)	(.43)	(.4303)	(.4249)	(.452)
Past employment conditions						
Years at last company	.8612	.9318	.9681	1.0849	1.1233	.8526
	(4.3991)	(4.409)	(4.4971)	(4.83)	(4.783)	(4.3862)
Not at a company	.1195	.1522	.1642	.1684	.1962	.1139
	(.3244)	(.3593)	(.3706)	(.3744)	(.3975)	(.3176)
Small company	.1954	.1994	.1933	.1898	.1792	.1931
	(.3965)	(.3996)	(.395)	(.3923)	(.3839)	(.3947)
Medium company	.237	.2329	.2393	.238	.2321	.2368
	(.4253)	(.4227)	(.4268)	(.426)	(.4226)	(.4251)
Large company	.365	.3512	.3351	.3414	.3245	.3663
	(.4814)	(.4774)	(.4721)	(.4744)	(.4686)	(.4818)
One-man company	.0301	.0289	.0294	.0312	.0377	.0305
	(.1709)	(.1676)	(.1691)	(.1739)	(.1907)	(.1718)
Person-specific variables						
Age	51.801	52.0622	52.0415	52.0829	51.9585	51.7571
	(5.4312)	(5.2731)	(5.2616)	(5.3974)	(5.52)	(5.4618)
Immigrant	.1329	.1423	.153	.1542	.166	.1315
	(.3395)	(.3494)	(.3601)	(.3613)	(.3725)	(.338)
East German	.2567	.2592	.2489	.2424	.2151	.2563
	(.4368)	(.4382)	(.4324)	(.4287)	(.4113)	(.4366)
Female	.4349	.4499	.4388	.443	.4566	.4329
	(.4958)	(.4975)	(.4963)	(.497)	(.4986)	(.4955)
Living with partner	.7776	.7757	.7681	.7594	.7434	.7747
	(.4158)	(.4172)	(.4221)	(.4277)	(.4372)	(.4178)

Table 7 reports summary statistics of all variables used in the empirical analysis disaggregated by changes in health satisfaction. Column (1) states the mean values of the sample, Column (2) states mean values for those who experience a health deterioration between the past and current period, Column (3) to (5) state the mean values of those individuals who experienced a health deterioration of 1, 2, or 3 units, respectively. Column (6) states the mean value for those whose health remain constant.

Table 8: Health shock constructed from health satisfaction

	No Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog
				Locus of control			
		Definition 1		Definition 2		Definition 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lvert\Delta_{HS,t-1}\rvert > 1\sigma_{HS}$							
Pooled binary logit							
Health shock	0.026						
	(0.007)***						
Separation between internals and externals							
Health shock internals		0.015	0.022	0.015	0.022	-0.003	0.012
		(0.008)**	(0.008)***	(0.008)**	(0.008)***	(0.010)	(0.012)
Health shock external		0.049	0.033	0.049	0.033	0.042	0.032
		(0.014)***	(0.012)***	(0.014)***	(0.012)***	(0.009)***	(0.008)***
Internals			-0.019		-0.020		-0.023
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	19.24	4.87	12.54	4.87	13.05	9.87	23.57
P-Value	0.00	0.03	0.00	0.03	0.00	0.00	0.00
$\Delta_{HS,t-1} \leq -3$							
Pooled binary logit							
Health shock	0.027						
	(0.010)***						
Separation between internals and externals							
Health shock internals		0.023	0.030	0.023	0.030	0.007	0.025
		(0.011)**	(0.012)**	(0.011)**	(0.012)**	(0.014)	(0.016)
Health shock external		0.035	0.019	0.035	0.019	0.037	0.027
		(0.018)*	(0.016)	(0.018)*	(0.016)	(0.013)***	(0.012)**
Internals			-0.020		-0.021		-0.025
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	9.65	0.35	12.38	0.35	12.96	2.37	22.40
P-Value	0.00	0.55	0.00	0.55	0.00	0.12	0.00

Table 8 reports the marginal effects of a health shock on the probability of current period inactivity. The health shock is defined by either 1 standard deviation of health deterioration from the sample average of health satisfaction ($\lvert\Delta_{HS,t-1}\rvert > 1\sigma_{HS}$) or by health deteriorations of at least 2 units of health satisfaction from one to another period ($\Delta_{HS,t-1} \leq -3$). Inactivity is defined as all individuals who are either registered unemployed, retired or currently searching for new employment. All models control for age, gender, immigrants status, living in East Germany, last period household wealth and income proxied by owing stocks, having savings, and the log of household income, last period employment characteristics, living with a partner, partner's employment status, human capital indicators, and year dummies. Model (1) assumes a homogeneous effect of a health shock across personality types (No Heterog). Model (2) allows the effect to differ between internals and externals, but assumes that both face the same unemployment probability in the absence of the shock (Intercept homog). Model (3) assumes that the overall inactivity probabilities differ between internals and externals (Full heterog). F-Statistic and P-value report test whether the marginal effects of the health shocks differ between internals and externals in Model (2), (3), and (4): $H_0 : \delta_o = \delta_p$ and in Model (3), (5), and (7): $H_0 : \delta_o = \delta_p$ & $\alpha_o = \alpha_p$. Robust standard errors are reported in parentheses. * 10 %, ** 5 %, *** 1 % significance level.

Table 9: Health shock constructed from number of doctor visits

	NO Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog	Intercept Homog	Full Heterog
				Locus of control			
		Definition 1		Definition 2		Definition 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lvert\Delta_{DV,t-1}\rvert > 1\sigma_{DV}$							
Pooled binary logit							
Health shock	0.063						
	(0.009)***						
Separation between internals and externals							
Health shock internals		0.049	0.057	0.049	0.057	0.037	0.058
		(0.010)***	(0.011)***	(0.010)***	(0.011)***	(0.015)**	(0.016)***
Health shock externals		0.089	0.070	0.089	0.069	0.075	0.062
		(0.017)***	(0.015)***	(0.017)***	(0.015)***	(0.011)***	(0.010)***
Internals			-0.019		-0.019		-0.023
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	79.51	4.16	11.71	4.16	12.23	3.88	20.95
P-Value	0.00	0.04	0.00	0.04	0.00	0.05	0.00
$\Delta_{DV,t-1} \leq -3$							
Pooled binary logit							
Health shock	0.037						
	(0.006)***						
Separation between internals and externals							
Health shock internals		0.025	0.031	0.024	0.031	0.015	0.032
		(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.009)	(0.010)***
Health shock external		0.062	0.045	0.063	0.046	0.048	0.037
		(0.011)***	(0.010)***	(0.011)***	(0.010)***	(0.008)***	(0.007)***
Internals			-0.018		-0.018		-0.023
			(0.006)***		(0.006)***		(0.005)***
Observations	32224	32224	32224	32224	32224	32224	32224
F-Statistic	55.67	7.68	12.43	8.39	13.15	7.04	21.21
P-Value	0.00	0.01	0.00	0.00	0.00	0.01	0.00

Table 9 reports the marginal effects of a health shock on the probability of current period inactivity. The health shock is defined by either 1 standard deviation of health deterioration from the sample average of number of doctor visits ($|\Delta_{DV,t-1}| > 1\sigma_{DV}$) or by health deteriorations of at least 3 units of doctor visits from one to another period ($\Delta_{DV,t-1} \leq -3$). Inactivity is defined as all individuals who are either registered unemployed, retired or currently searching for new employment. All models control for age, gender, immigrants status, living in East Germany, last period household wealth and income proxied by owing stocks, having savings, and the log of household income, last period employment characteristics, living with a partner, partner's employment status, human capital indicators, and year dummies. Model (1) assumes a homogeneous effect of a health shock across personality types (No Heterog). Model (2) allows the effect to differ between internals and externals, but assumes that both face the same unemployment probability in the absence of the shock (Intercept homog). Model (3) assumes that the overall inactivity probabilities differ between internals and externals (Full heterog). F-Statistic and P-value report test whether the marginal effects of the health shocks differ between internals and externals in Model (2), (3), and (4): $H_0 : \delta_o = \delta_p$ and in Model (3), (5), and (7): $H_0 : \delta_o = \delta_p$ & $\alpha_o = \alpha_p$. Robust standard errors are reported in parentheses. * 10 %, ** 5 %, *** 1 % significance level.

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