Can Subjective Well-Being Predict Unemployment Duration?

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Abstract

This paper uses 16 waves of panel data from the British Household Panel Survey to evaluate the role of subjective well-being in determining labor market transitions. It confirms a previous finding in the literature: individuals report a fall in their happiness when they lose a job, but they report a smaller fall when they are surrounded by unemployed peers, an effect called the "social norm". The main results of interest are that job search effort and unemployment duration are affected by the utility differential between having a job and being unemployed. Since this differential is also affected by the social norm, it implies that when unemployment increases, the unemployed are happier and they reduce their search effort. These results indicate that unemployment hysteresis has labor supply causes.

***An update to the paper introduces the 2008-2010 data and uses the sharp UK recession to further test the social norm of unemployment, as well as its effects on job search and labor supply.

Keywords : Subjective Well Being, Job Search, Unemployment Duration, Social Norms, Comparisons
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1 Introduction

This paper aims at showing that labor supply decisions are often made taking into account other's labor supply, due to the existence of strong comparison effects. It also goes one step further in showing that job search effort is affected by comparisons with others. The dataset used is the BHPS (British Household Panel Survey). It is a representative sample of the British population, from which labor market status and a composite measure of self-reported well-being (to proxy for utility) are used.

Three distinctive results are presented. First, it is shown that upon losing their job, individuals report a fall in their well-being. This fall is reduced when there are more unemployed in one's comparison group (household and region), referred to as the "Social Norm Effect", as in Clark (2003). This effect persists in panel data estimations were the unobserved individual heterogeneity is controlled for. The second finding is that unemployment duration is affected by this social norm effect. The more an individual reports feeling hurt when losing his job -(the happiness difference)- the shortest will be his duration in unemployment. The happiness difference is a good predictor of the duration of unemployment, even after controlling for demographic characteristics also affecting duration. The third result shows that job search effort is itself dependent on the happiness difference. An individual searches with more intensity when he reports a large happiness drop when entering unemployment.

The implications of these results are twofold. First, they shed light on our understanding of job search effort. The results suggest that search effort is positively dependent on $V_e - V_u$, the difference in well-being an individual reports between being employed and jobless. As the payoff from being employed rises (falls), the unemployed will search more (less). Second, they provide a labor-supply explanation of unemployment hysteresis. Due to comparison effects, when an individual loses his job, he feels less bad if there are more unemployed around him. His utility is hence affected by other's employment status. This will reduce his search effort and increase his unemployment duration, affecting then the search behavior of others. In the case of an exogenous macroeconomic shock that reduces labor demand, our findings suggest that labor supply will also shift to the left, *increasing unemployment* and causing hysteresis.

The remaining of the paper is organised as follows. Section 2 provides a review of the literature on subjective well-being (SWB henceforth) and labor market status. Section 3 describes the 16 waves of the BHPS. Section 4 shows the first results of importance. It first presents the determinants of SWB, and then the social norm effect. Both pooled and panel data specifications are explained. Section 5 introduces the determinants of unemployment duration and search effort. Section 6 concludes.

2 Literature Review

This section reviews the literature on subjective well-being (SWB) and labor market status. It summarizes two main findings, both relevant for the present thesis. The first finding is that individuals' happiness is affected by their employment status. Those who lose their job feel significantly worse than when employed, far worse than their income loss would predict [1]. The second finding is that aggregate unemployment is also affecting individuals. There is a so called "Social Norm" effect of unemployment, through which unemployed feel less hurt the higher the unemployment is in their reference group. Unemployment also affects those who are employed, although contradictory effects are found in the literature [2]. Based on these findings, this section presents the possibility that the social norm effect from unemployment might affect the search behaviour and the duration of unemployment. It then asks what policy questions arise.

2.1 Subjective Well-Being and Labor Market Status

A large stream of research has been interested in the relationship between subjective well-being and labor market status. The social psychology literature precedes economics in this field. The idea conveyed in most of the works is that there are many non-pecuniary benefits from working. Unemployment deprives the former workers from latent functions such as social interactions, purposefulness, a time structure and a certain construction of identity Jahoda (1982). Hence, unemployed are worse off not just because of the loss of their wage income[3]. Earlier empirical work by Jackson, Stafford and Warr (1983) shows that well-being rises with the transition from unemployment to paid work. Although the sample used is not representative of the population, it is useful at highlighting the effect of transitions on happiness. Darity and Goldsmith (1996) provide an extensive summary of the social psychology literature on unemployment.

Empirical work from economists testing this view has been conducted since the early 1990s, when data on SWB became available through national household surveys including a section on well-being. Clark and Oswald (1994) use the first wave of the BHPS to find that unemployed are, on a raw average, half as happy as the employed. This result is corroborated by the studies of Korpi (1997), who uses Swedish data, Winkelmann (1998), who use the German GSOEP, Woittiez and Theeuwes (1998) who have Dutch data, Frey and Stutzer (2001) who use a Swiss household survey, and Blanchflower (2004) for Britain

[1] Clark and Oswald (1998) finds that the income loss from losing a job explains only a quarter of the drop in well-being

[2] Rafael Di Tella Robert J. MacCulloch (2001) find that unemployment negatively affects SWB (in developed countries), whereas Eggers et al. (2006) find a positive effect using Russian data.

[3] Proponents of this idea highlight the negative psychological impact of being unemployed. Summaries of the literature can be found in Fryer and Payne (1986), Warr *et al* (1988), Feather (1990), Burchell (1992), Murphy and Athanasou (1999). Argyle (2002) is a reference book in social psychology with an extensive chapter on the GHQ measure and another one on unemployment

and the USA. Data on other countries have also been available through the World Values Surveys (WVS) and in other European studies such as the ones used by Blanchflower (2001) for Eastern and Central Europe, and DiTella et al. (2001) for Europe and the USA. What all these studies have in common is the result of lower levels of well-being for the unemployed.

A reverse causality issue can arise if one is limited to cross section data, as it might be easier for happy people to find a job. If inherently happy people are also more productive, better at work or simply more desirable to employers, then it is happiness that positively influences the chances of finding a job, and not the reverse. One way to isolate the causal impact is to use panel data and observe what happens to individuals' happiness as they change status. This identification strategy is followed in this paper, and the panel data evidence on labor market transitions proves that the causality goes from labor status to happiness rather than the other way around.

2.2 The Social Norm Effect of Unemployment

Individuals are affected by their employment status, but also by others' employment. DiTella et al. (2001) are among the first to test the impact of aggregate unemployment on individual's well-being. They find that people have a preference for lower levels of aggregate unemployment. Their results, to be interpreted in a context of a tradeoff between inflation and unemployment (a phillips curve), show that individuals are also hurt by inflation although its effects are much lower. The finding is consistent with the literature on happiness in the sense that it provides evidence of strong comparison effects.

The classical analysis of Akerlof (1980) has been instrumental in the way economists think about social norms, their sustainability and their effect on individual's behavior. In his model, a social norm precluding transactions at the market-clearing wage can cause unemployment and still be sustainable if deviation from the norm is costlier, in terms of reputation, than the monetary benefit from adhering to it. The higher the proportion of followers of the norm, the more sustainable it is - as it becomes more costly to deviate. Following this theoretical conclusion, the question that arose was whether or not employment can be considered as a social norm. Supposing it can be, then it can be tested whether unemployment hurts more if one's reference group has little of it - that is if the norm is not followed.

Clark (2003) provides strong evidence supporting this hypothesis. He finds that in the U.K. unemployment at regional, partner and household level affects positively and strongly the well-being when the respondent is unemployed, the effect being higher for men. This finding has been tested in other countries, and similar results are found in Russia Eggers et al. (2006) and in South Africa in Powdthavee (2007).

Stutzer and Lalive (2004) also test Akerlof's theory. They instrument for the unobserved social norms by using a referendum on unemployment benefits to extract the voting patterns across localities in Switzerland, to proxy for social norms. To correct for the potential reversed causation (regional unemployment causes the norm) they use a stratified approach, which is the variation in the proxy accounts for variation within regions. Their results suggest that, indeed, in cantons voting to reduce benefits (strong work ethic), the unemployed were more likely to find a job than in cantons voting for a rise in benefits (weaker work ethic). For those not having the same native language as the canton, the effect was lower. These results emphasize the view that unemployment can be interpreted as a social norm.

Given that unemployment reduces happiness, but that an increase in unemployment in the reference group attenuates this negative impact, the question has been raised to know whether the duration of unemployment is affected by the level of it in the individual's reference group, broadly defined. This will be the main focus of this paper.

2.3 Unemployment Duration and Subjective Well-Being

To know how SWB is related to unemployment duration, many papers ask if duration affects SWB; because it is relevant to know whether or not individuals adapt to unemployment. Clark and Lucas (2006) finds that there is no (or little) evidence of habituation. After the initial drop in well-being when losing a job, individuals do not become happier with time unless they change status.

There is however another channel through which well-being and duration might be related. Looking for a job entails a costly effort, needing investment in readings ads, writing applications, mobilising one's network, etc. If the utility differences between states (employed and unemployed) is small, it might not be worth suffering the search cost for an outcome that is uncertain. This paper shows that in high unemployment regions, SWB falls less when individuals lose their job. Hence, the incentive to return to work is reduced, since the utility difference is smaller. This might affect search behavior, and unemployment duration might be longer, affecting in turn the behaviour of others in a self-reinforcing fashion. This mechanism is very similar to the one described in Akerlof (1980). If the norm is employment, and it is not much followed, there are less bad reputation effects from not following it. It suggest that shocks matter because they affect the labor supply behaviour. If this story holds, then there is a continuum of equilibria - as one's status affects other's search behaviour. The present thesis attempts to find whether or not the job search behaviour (and unemployment duration) is affected by the social norm effect. Future research should aim at modelling labor supply and job search including externalities - to capture the effect mentioned above.

3 Data Description

The data set used in this paper is the British Household Panel Survey (BHPS). The data is collected on households and individuals aged 16 or older, once a year between the months of September and May. It covers a representative sample of the British population during 16 years (1991-2006), providing information on almost 10.000 households over the period. For waves 1 to 8 there are around 10.000 individual observations by year, whereas for waves 9-16 there are on average 15.000 yearly individual observations[4] . This means that the panel is unbalanced: during the sixteen years of the survey, some households and individual leave while others enter the sample.

We keep in the sample individuals aged between 21 and 65 years who are active in the labour force - either working or actively looking for a job. Given that we keep only working age population, the mean age in the sample changes to around 40 years old, as opposed to 45 for the whole survey. Table 11 in the appendix provides a summary of statistics for the variables in the survey.

The measure of well-being used is derived from the General Health Questionnaire (GHQ). It has been designed by Goldberg (1972), and is widely used by psychiatrists to assess a person's well-being. The 12 questions asked are provided in the appendix. As presented by Argyle (2002) the GHQ is one of the most reliable indicators of psychological distress. I use an "inverted Caseness score"[5]. The distribution of this variable is given in Table 12, in the appendix. It is observable that the distribution is highly skewed to the top, with most of the respondents scoring 12, the highest possible grade. Only a quarter (26 %) scores less than 10. Looking at the distribution of GHQ by employment status in Table 1 and Figure 1, one can note the following two facts. First, the mean of GHQ is significantly lower for unemployed persons, if one compares them to the employed or self-employed population (9,1 for the unemployed vs. 10,4 for the employed and 10,1 for the whole population sample.). Second, the distribution of GHQ has a larger variance in the unemployed group, where 26% of the respondents declare a low well-being (defined as a score inferior to 8), against 13% and 12% for the employed and self-employed. These distributional characteristics are clearly presented in Table 1 and Figure 1, below.

[4]In 1999, 1500 households were added from both Scotland and Wales. In 2001, another 2000 households were added from Northern Ireland. More information can be found on the BHPS at http://www.iser.essex.ac.uk/survey/bhps

[5]There are 12 questions, and the score ranges from 0 to 12. Individuals start with a score of 12, and for each question in which they are fairly or highly stressed, they lose a point. Psychiatrists use the GHQ : individuals with low levels of Caseness are eligible for their treatment (Argyle, 2002).

Table 1: Subjective Well-Being by Labor Force Status

Current Labor Status	Mean SWB	std.dev	observations	% low SWB
Self-Employed	10,4	0,024	12598	12,3
In Paid Employment	10,3	0,009	92646	13,4
Unemployed	9,1	0,004	6474	26,0
Total	10,1	0,008	147698	16,1

Source: BHPS, waves 1-16. "Low SWB" is defined as lower than a score of 8.
T-tests between the mean of SWB of the unemployed and the other two labor categories confirm that they are different at the 1% level.

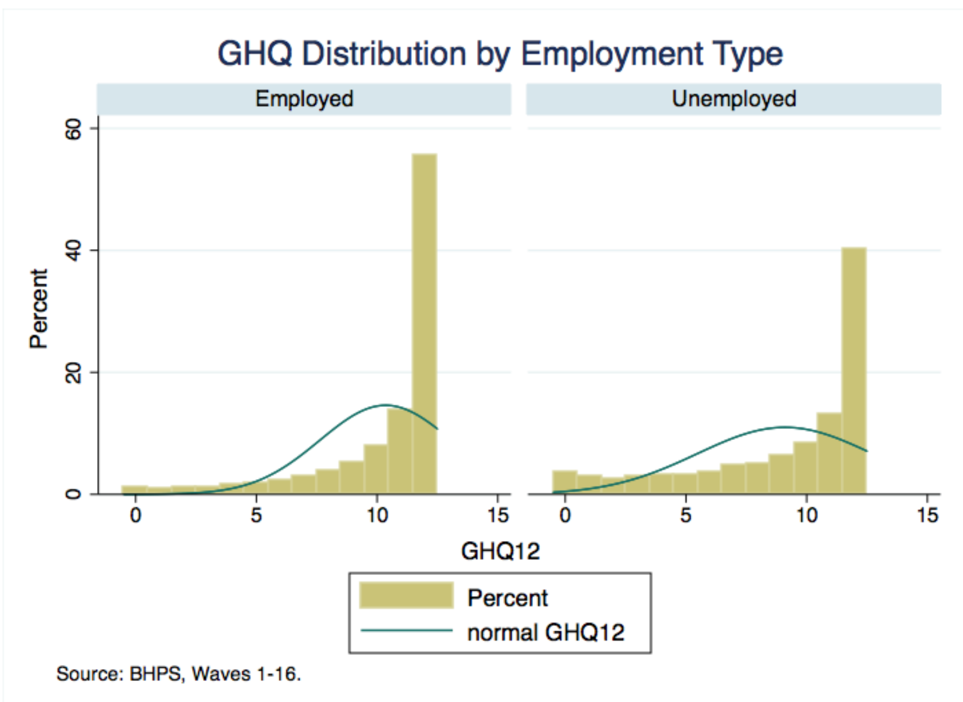

Figure 1: Distribution of GHQ

4 Determinants of Subjective Well-Being

Subjective well-being is obviously not only related to employment status. A multivariate approach is necessary. Income, health, age, education, and civic status are all likely to directly affect an individual's well-being. As the GHQ caseness score is an ordinal measure (it is not a continuous variable), a linear probability model is not the best tool to estimate its determinants [6]. An ordered probit regression is used to complement the results of the OLS regression, and the results from both methods will be discussed below. The results on the main determinants of SWB are in regression Table 2, which shows the ordered probit estimation. The results from the OLS regression are very similar and are in Table 13 in the appendix. Three specifications are presented for both cases, in which the explained variable is subjective well-being.

The three OLS equations estimated are shown below. S_i stands for labor market status; Y_i for income; $Educ_i$ for educational achievement, the reference category being no diploma. $Health_i$ stands for the health status, the reference being excellent health. The reference dummy for civic status is never married and X_i stands for the control of all previous variables.

$$W_{it} = \beta_0 + \beta_1 S_{it} + \epsilon_i t \tag{1}$$

$$W_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 Y_{it} + \beta_3 Male_{it} + \beta_4 Age_{it} + \beta_5 Age^2_{it} + \beta_6 Civic_{it} + \beta_7 Health_{it} + \beta_8 Educ_{it} + \epsilon_i \tag{2}$$

$$W_{itj} = \beta_0 + \beta_1 S_{it} + \beta_2 X_{it} + \beta_3 Year_j + \beta_4 Region_k + \epsilon_i \tag{3}$$

In the first specification, labor market status is the only regressor, for which the reference category is "Employed". The coefficients indicate that the self-employed are slightly but significantly happier than the employed, when other life variables are not controlled for. The unemployed are the least happy. In the OLS regression, they have around 1.2 points less of well-being than the employed. The coefficients of the ordered probit indicate that Unemployed are 40% less likely to have a score of 12 than the employed, when controlling for other factors. In the second specification controls are added for the list of individual characteristics mentioned above. In the third specification, children dummies, year and region fixed effects are included. The results in all three specifications are in line with those found in Clark (2003) using the first seven waves of the BHPS.

[6] because the distribution of the disturbance term is not normal anymore - standard errors and t-stats are thus invalid. An ordered probit increases the fit and provides reliable z-stats, instead of the t-stats.

Table 2: SWB and Labor Force Status - Ordered Probit

	Simple	Some Controls	Broad
Self-Employed	0,04	-0,046	-0,04
	(3.70)**	(4.09)**	(3.57)**
Unemployed	-0,433	-0,412	-0,409
	(31.29)**	(28.29)**	(28.00)**
Annual Income in 'k		0	0
		-1,37	(2.46)*
Male		0,209	0,213
		(28.97)**	(29.23)**
Age		-0,021	-0,021
		(8.70)**	(8.19)**
Age Sq./100		0,319	0,308
		(11.13)**	(10.09)**
Married		0,019	0,03
		(1.99)*	(2.78)**
Separated		-0,32	-0,329
		(14.45)**	(14.67)**
Divorced		-0,08	-0,07
		(5.51)**	(4.69)**
Widowed		-0,194	-0,18
		(6.13)**	(5.64)**
Health : Good		-0,244	-0,245
		(28.98)**	(28.86)**
Health : Poor		-0,8	-0,8
		(77.65)**	(77.40)**
Education : High		-0,174	-0,186
		(18.22)**	(19.17)**
Education : Medium		-0,084	-0,093
		(8.57)**	(9.40)**
Children Dummies	No	No	Yes
Wave Dummies	No	No	Yes
Regional Dummies	No	No	Yes
Observations	111761	110140	109390

Source: BHPS, waves 1-16, pooled data.
Absolute value of z statistics in parentheses. * significant at 5%; two * significant at 1%
Reference dummy for labor market status is "Paid Employmen"t ; for civic status is "Never Married" ; for health is "Poor" and for Education "Low".

4.1 Labor Market Status, Age, Income, Civic Status, Education and Health

In all specifications, the coefficient for males is positive and significant (0.5 points higher than females). This indicates that men self-report higher levels of well-being than women. This is also visible in the raw mean, where men are 0.5 points happier than women. The effect of age is U-shaped and bottoming in the late thirties, confirming the results found in the literature on age and happiness [7]

Consistent with most of the literature findings, the effect of marriage is slightly positive, while being separated, divorced or widowed is on average associated with a lower well-being. The channels through which marriage *causes* the rise in well-being are explained in Argyle (2002). An intimate relationship enhances self-esteem and it can attenuate stress from other life activities like one's job. However, the coefficients presented here should not be seen as a causal effect, as it could also be possible that being inherently happy favors one's marriage prospects. To isolate the causal effect of marriage or divorce, different options have been used. Clark and Lucas (2006) look at transitions between civic states using the GSOEP, and find that marriage increases happiness but that a habituation effect exists. The prospect of marriage (cohabitation) raises well-being 3 years before marriage, but this increase in happiness does not last longer than 3 years after the marriage date. Finally, Stutzer and Frey (2006), identify the causal relationship of mariage on SWB by getting rid of the selection bias into mariage. Also using the GSOEP, they control for the selection of happier people into mariage to estimate the causal effect. Their results are similar to those of Clark and Lucas (2006). [8]

The effect of income on SWB is particularly interesting. As found in Easterlin (1974, 2001), income is a poor estimator of happiness. The results found in the literature suggest that relative income matters more than income itself, and income growth is important but not its level (above a certain threshold). These results highlight the role of comparisons, to others and to oneself in the past. The coefficients we find are negative and insignificant, confirming this story. However, when one goes from specification 2 to specification 3, the coefficient remains negative and becomes slightly significant. This suggests that a higher income might be associated with other variables that we are not controlling for (such as hours of work) that are negatively correlated with SWB. In the appendix a specification controlling for relative income is presented. Being in the top quarter of the wage distribution has no significant impact on well being. The effect of education is also interesting.

[7] On the U-shaped relationship between age and SWB, see Blanchflower and Oswald (2008), as well as earlier results in Clark and Oswald (1994), Frey and Stutzer (2002), Winkelmann (1998).

[8] Which gender benefits more from marriage has been subject to intense debate. Bernard (1972) proposed that men benefit much more from marriage than women. Glenn (1975) shows the opposite. More recent findings (Fowers, 2004) using subjective well-being data confirm Bernard's 1972, while others show that marriage increases happiness equally between genders.

The higher the achievement the lower the SWB. The current explanation is that a higher diploma leads also to higher income expectation, which reduces satisfaction for a given level of income. (see Argyle, 2002, and Frey and Stutzer, 2001, on expectations).

Table 3 reports the results for the effect of labor transitions on SWB. We observe that upon losing their job, those who were employed report on average a drop of 1,08 in their SWB, and 0,91 if they were self-employed. This is a significant fall, given how the distribution is skewed to the right. The transitions from unemployment to employment or self-employment are associated with large increases in well-being (correspondingly 1,41 and 1,20 points). People do feel better when they find a job.

Table 3: Transition Matrix - Change in Labor Status and in Well-Being

	Labor Status in t		
Labor Force Status in t-1	Employed	Unemployed	Self-Employed
Employed			
Mean	-0,05	-1,08	0,03
Std.Err	0,011	0,106	0,073
N	70 175	1 419	1 486
Unemployed			
Mean	1,41	-0,01	1,20
Std.Err	0,095	0,079	0,236
N	1 552	1 928	239
Self-Employed			
Mean	0,22	-0,91	-0,04
Std.Err	0,085	0,280	0,030
N	1 299	184	8 401

There is however an asymmetry in this process. On average, individuals report a larger gain in well-being when returning to work than the loss they report when losing it. This asymmetry is an interesting behavioral fact also found in Clark (2003). No references have been found in the literature pointing towards this asymmetry. [9] In the appendix, Tables

[9] There are two possible explanations for this asymetry. A first explanation could be that upon finding a job people are overconfident, so they report a high jump in well-being. It could also be that when losing a job, people are confident they will find another one quickly, so they don't worry too much. In any case, the asymmetry means that jobs are less valued when they are lost than when they are filled. In job search theory, the present value of unemployment or of a position is independent of whether the position is filled. Perhaps jobs created are more valuable than jobs destroyed - hinting at the possibility of a Schumpeterian creative destruction process.
A second possibility is to explain this asymetry by anticipation and adaptation effects, an approach taken

15 and 16 show the same transitional matrix for each gender separately. The pattern by gender is the same, but males report higher drops and peaks than females. Transitions from unemployment to employment provide males with a 1.6 jump in SWB, compared to a 1.15 for females. When they lose their job, males report a drop of 1.15 points compared to a 1 point drop for females. The transition from self-employment to employment gives much greater rewards to females (0.4 points more) than to males (0.1), which could be interpreted as a more risk-loving behavior of men.

4.2 The Social Norm Effect of Unemployment

The literature on happiness highlights the important role of comparisons in individuals' well-being. It is income relative to others that matters or to oneself in the past. A slightly different comparison mechanism is at play when it comes to labor market status, but comparisons are still present. The previous section shows that the transition from employment to unemployment is causing a drop in SWB. Furthermore, there is no habituation effect : the unemployed feel on average significantly worse than those in employment, even after controlling for other factors[10]. Aware of this pattern, a relevant question arises. How does other's employment affects one's well-being ? Are those losing a job also comparing themselves to others in unemployment? If yes, in what ways ? Finally, do these comparisons affect their job search behavior ?

4.2.1 Theory : a binary choice model with externalities

As in Akerlof (1980) social norm model, we can add others' behavior and beliefs in the utility function. Whereas previous well-being estimations were only accounting for personal unemployment (U_e) and were of the form $W_i = W(U_e, X)$, we are now interested in a utility function including a norm, beliefs and reputation effects, such that

$$W_i = W(G, R, A, d^c, \epsilon)$$

Agent's utility W_i is dependent on their private consumption G, their reputation R, their belief in the norm d^c, obedience to the norm A(1,0), and personal tastes ϵ. Let us suppose that reputation depends itself on the proportion of believers μ and one's own actions A, such that $R = R(\mu, A)$. If everyone believes in the norm ($\mu = 1$) and agent i does not follow it (A=0), he suffers from reputation effects. As less people believe in the norm, the reputation effect from not following it is reduced and this in turn pushes more people not to obede. As Akerlof explains, if there are no reputation effects, the only possible equilibria are derived from the traditional utility function with tastes ϵ and

in Hanglberger and Merz (2011) who find existence of large and negative anticipation effects of losing a job.

[10] Clark (2006) finds that unhappiness does not decrease with unemployment length using the GSOEP and the ECHP, but has mixed results using the BHPS

consumption G. However, if deviation from the norm is costly in terms of reputation, we may have a stable equilibrium in which the norm is self-sustained and agents follow it. It is a simple example of a binary choice model with externalities, in which two equilibria are sustainable.

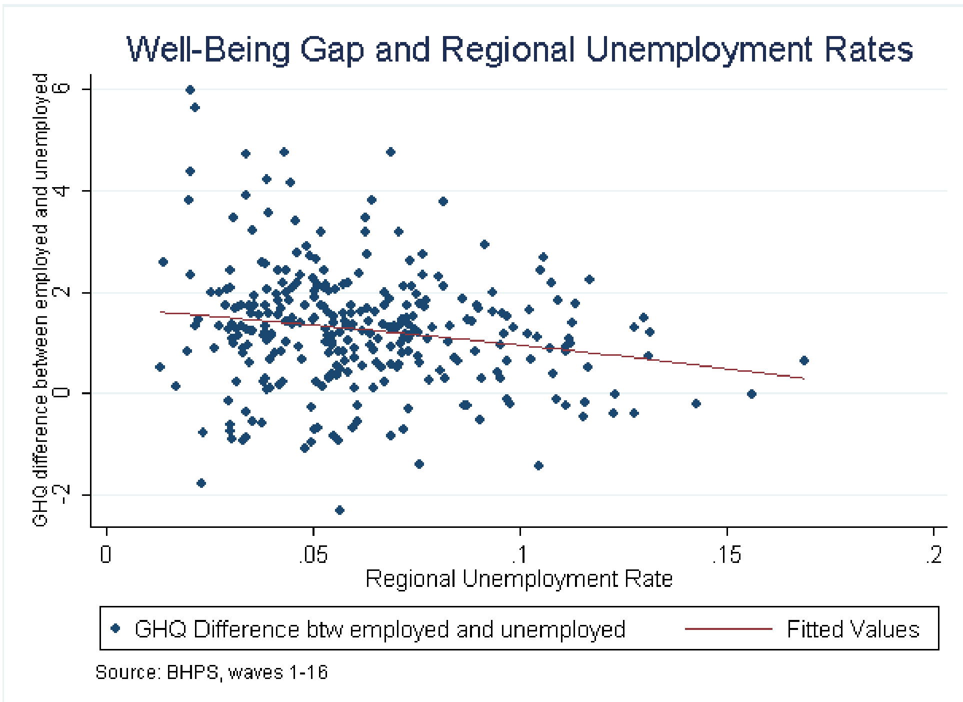

Figure 2: Employed-Unemployed GHQ gap, as function of regional unemployment

In this case the norm is employment. The adherence to the norm, μ is the employment rate. This follows Akerlof's model in the sense that if all other adhere to the norm, there is a bad reputation effect from not following it. As the number of unemployed rises, the stigma from being unemployed falls. Clark (2003) considers a linear form for reputation : $R = (-Ue_i(1 - Ue_i^*)$. We follow his steps here, and the main equation is :

$$W_i = W_i[-Ue_i(1 - Ue^*), 1 - Ue^*, X]$$

This allows for the following effects. Being unemployed hurts (through the first term), a rise in the unemployment rate hurts (through the second term), but it improves well-being if one is unemployed (again first term).

4.2.2 Empirical evidence : pooled data regressions

Figure 2 shows a simple plot of regional/yearly unemployment rates and the average well-being difference between employed and unemployed. The correlation is quite visible at eye-level. In regions/years where unemployment is high, people report being less hurt when they lose a job. Table 14 shows the regression results in the appendix: a 1% increase in unemployment corresponds to a 0.08 points drop in the loss of happiness. A first empirical glimpse of this relationship was found in Clark and Oswald (1994), though they used only the first wave of the BHPS. They were unable to reject the shift-share hypothesis[11]. Clark (2003) uses the first seven waves of the BHPS to confirm this early prediction. He finds that in regions with high unemployment, SWB falls less when losing a job. The same result is found in this paper, extending the sample to 16 waves of the BHPS.

This finding suggests that unemployment hurts - but it hurts less the more there is of it around. It suggest that labor market status is one important comparison affecting well-being. The question often posed is who do people compare to ? Who are the relevant others ? Is it the whole population or the people on the neighbourhood? Is those of same sex, age, income and educational achievement? Data on relevant others from the survey can be used to test if employment in the reference group is also affecting well-being when losing a job. The OLS estimations to test the hypothesis are the following.

$$W_{it} = \beta_0 + \beta_1 U_{it} + \beta_2 X_{it} + \beta_3 R_k U + \beta_4 (U_{it} * R_k U) + \epsilon_i \tag{4}$$

$$W_{it} = \beta_0 + \beta_1 U_{it} + \beta_5 X_{it} + \beta_6 U^* + \beta_7 (U_{it} * U^*) + \epsilon_i \tag{5}$$

$$W_{it} = \beta_0 + \beta_1 U_{it} + \beta_8 X_{it} + \beta_9 U^* + \beta_1 0 (U_{it} * U^*) + \epsilon_i \tag{6}$$

Where W_{it} stands for well-being of individual i at period t. X_i stands here for all other determinants, year, region and children fixed fixed effects. $U_{it} = 1$ when the respondent is unemployed. $R_k U$ stands for the regional unemployment rate; and $U^* = 1$ when the relevant other is unemployed. The interaction terms are expected to be positive.

Following Moulton (1986) the estimation uses clustered standard errors for the regional unemployment rates. This is because the regional unemployment rate is the same for all individuals within the region. If the clustering is ignored, the repetition of the same value in one variable is biasing downwards the standard errors and providing wrong t-stats.

The results of the regressions on pooled data are very straightforward. Table 4 below, shows the ordered probit results, while Table 17 in the appendix shows the OLS results. In the simple specification, one can see that the regional unemployment rate has no effect

[11] The shift-share hypothesis would hold if a rise in unemployment pushes the happier of the working force into unemployment.

on well-being. However, when one adds an interaction term between own unemployment and regional unemployment rate, the coefficient is positive and significant. This reflects the finding of the previous graph: unemployment hurts, but it hurts less the more there is of it around at the regional level.

The effect of spouse unemployment is also straightforward, and is presented in specification (3). Having an unemployed spouse significantly lowers one's well-being. The effect is 35 times higher than the regional unemployment interaction. But in specification (4), the interaction term between own unemployment and the spouse's unemployment is positive and significant : upon losing one's job, having an unemployed spouse is better than an employed one. The magnitude of the effect is also very high (above a quarter point). It tells us that individuals are hurt when losing their job, but they are hurt less if the reference group (here the spouse) is also unemployed. They also tell us that the spouse is a much closer reference group than the regional unemployment rate. The results of the broad specification show no difference in the coefficients, suggesting little multicollinearity between the two interaction terms.

Table 4: Well-Being and Other's Labor Force Status. Ordered Probit

	(1)	(2)	(3)	(4)
Self-Employed	-0,04	-0,04	-0,045	-0,045
	(3.55)**	(3.53)**	(3.68)**	(3.66)**
Unemployed	-0,409	-0,552	-0,549	-0,68
	(23.80)**	(13.19)**	(20.78)**	(12.18)**
Regional Unemployment Rate	0	-0,002	-0,002	-0,003
	(-0.2)	(-0.98)	(-0.54)	(-0.98)
Spouse Employed			0,074	0,074
			(6.55)**	(6.51)**
Regional Unemployment*Resp. Unemp.		0,021		0,02
		(3.45)**		(2.70)**
Spouse Unemployed * Resp.Unemp.			0,268	0,258
			(6.49)**	(6.25)**
Standard controls	Yes	Yes	Yes	Yes
Children dummies	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Observations	109461	109461	80850	80850

Source: BHPS, waves 1-16, pooled data.
Absolute value of z stat in parentheses. * significant at 5%; **, at 1%
Standard controls include income, age, health, education and civic status.

4.2.3 Empirical evidence : results with panel data specification

The results of the regressions using individual fixed effects are somehow less forward. Controlling for each individual's unobserved heterogeneity leads to losing as many degrees of freedom as individuals. As a result, the significance of some coefficients is lost. Table 5 presents the results of the regressions controlling for individual fixed effects (and Table 18 in the appendix shows estimations (1) to (12)). The results from the specifications (13) to (15) show that unemployment hurts men twice as more than women. The interaction term between own and regional unemployment is significant only for men, suggesting that women do not suffer from regional comparisons. The magnitude of the effect for men (0.04) is the same as in the previous specification using pooled data, in Table 17. Specifications (16) to (18) show that women suffer six times more than men from having an unemployed partner, both effects being significant, and quite high for women. The interaction term between spouse and own unemployment is positive and very strong for men, but small and insignificant for women. In other words, spouse's unemployment hurts more women than men, but men compare more to their spouses.

Table 5: Well-Being and Other's Labor Force Status - OLS w/ Fixed Effects

	All	Men	Women	All	Men	Women
	-13-	-14-	-15-	-16-	-17-	-18-
Self-Employed	-0,064	-0,112	0,025	-0,072	-0,143	0,053
	(-1,5)	(2.27)*	(-0,31)	(-1,48)	(2.61)**	(-0,56)
Unemployed	-1,234	-1,559	-0,744	-1,444	-1,783	-1,02
	(8.60)**	(9.21)**	(2.86)**	(15.70)**	(15.30)**	(6.94)**
Reg.Un.	-0,004	0	-0,01			
	(-0,71)	(-0,04)	(-1)			
Spouse Emp.				0,178	0,078	0,413
				(5.11)**	(2.06)*	(5.24)**
Spouse Un.*Un.				0,497	0,793	0,145
				(3.30)**	(4.89)**	-0,44
Reg.Un.*Un.	0,005	0,043	-0,058			
	(-0,24)	(2.01)*	(-1,53)			
Standard controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109461	56860	52601	81478	43082	38396
R-squared	0,45	0,45	0,44	0,45	0,45	0,44

5 Unemployment Duration

The BHPS has a separated detailed module on each employment/unemployment episode from every individual in the sample. Merging this data set with the previous yearly household survey makes it possible to run a duration model of both employment and unemployment spells in order to find the main determinants of duration. The sample is right-censored: information is not available on spells finishing after wave 16. Some random censoring also occurs as individuals are randomly lost during the 16 waves.

Over the 16 years of the sample, we have data on 5700 unemployment spells[12]. The average duration of a spell is 23 months, but there is a great heterogeneity as half of the spells end before the twelfth month and 70% of them before the 24^{th} month. The distribution is distinctly skewed to the right, artificially pushing the mean to 23 months. Table 6 summarizes some descriptive statistics on the spells, and Figure 3 shows the survival function of spells, decomposed by gender.

5.1 Determinants of duration

The observed duration of unemployment varies with some of the observed characteristics of the individuals, such as their gender, educational achievement, age, or region where they live.The differences between genders is very clear: women spend on average less time in unemployment. Selection issues are very likely to be the cause of this difference. Participation rates are higher for men than for women[13], so it is possible that working women differ significantly from their non-working peers, whereas this is less the case for men. Differences across regions are also evident. Unemployment duration is much higher in Scotland, Northern Ireland and Wales than in London and in the South. Age is a major determinant as younger individuals have shorter spells than older ones, in both genders. Finally, individuals with a higher educational achievement have on average shorter spells (15.4 months) than the low achievers (32.1 months).

Figures 3 and 5 provide visual evidence of two clear discontinuities in the rate of return to work. The first discontinuity is found in the months 10 and 11, in which the rate of return to work is significantly higher than in the immediate preceding or following months. The main suspect for causing this discontinuity is the reduction in benefits occurring on the 12^{th} month. The same story applies for months 22 and 23, as the benefits are also reduced on the 24^{th} month. For some individuals, monetary incentives seem to play a significant role in the rate of return to work. To summarize: age, gender, region and educational

[12]Spells longer than 12 years are (arbitrarily) taken out of the sample. They are outliers irrelevant to the present analysis and bias the results

[13]Women's participation rates have increased from 70% to almost 75% between 1991 and 2006 (the years covered in this survey). Men participation rates are above 85%

achievement all seem to be correlated with unemployment duration. Monetary incentives also play a direct causal role, as the anticipation of a drop in benefits causes some individuals to return to a paid job. These results are in line with the literature on job search behavior. The theoretical model of Mortensen (1977) predicts a rise in the hazard ratio as one gets closer to the benefits exhaustion time. Meyer (1990) finds evidence of large spikes in the hazard in the prior weeks before exhaustion, a result that is also shared by a large amount of literature [14]

In the next subsection it will be asked how unemployment duration and well-being are related. As duration spent in unemployment and well-being can influence each-other, it is difficult to isolate the impact of one on the other. Individuals might suffer when they lose their job, but perhaps they also get used to be unemployed. Hence, we could observe that time spent on unemployment has a positive effect on well-being. A reverse mechanism could also exist. The well-being difference between the two states can play as an incentive to return to work. As the gap of well-being increases between being jobless and employed, the incentive to find a job increases, thus reducing duration. Understanding which of these stories is true (both can be) is important for both policy and research reasons, as it will be explained below.

[14] Moffitt (1985), Meyer (1990), Ours and Vodopivec (2006), Dormont and Fougère (2001) all find, using data from different countries, that the exit rate from unemployment to employment rises sharply as the end of the entitlement period approaches. See Card et al. (2007) for a review of findings.

Table 6: Unemployment Duration, Measured in Months

	Men (Std.Dev)	Women (Std.Dev)	All (Std.Dev)
Average	26.9 - (31.9)	18.0 - (23.7)	23.7- (29.6)
6 months or less %	29.2	35.0	31.2
12 months or less %	46.3	61.5	51.7
24 months or less %	65.4	79.6	70.4
Region			
Inner London	28.3 - (26.1)	18.0 - (21.8)	24.3 - (25)
Rest SE	21.9 - (27.6)	13.2 - (15.7)	18.2- (23.7)
South West	21.0 - (27.7)	12.1 - (12.8)	17.9- (24.0)
Scotland	30.9 - (37.6)	20.6 - (26.7)	27.0- (34.3)
Wales	27.6 - (32.5)	24.0 - (32.7)	26.3 - (32.6)
N.Ireland	27.2 - (33.6)	25.6 - (32.6)	26.6 - (33.2)
Age			
Age $\geq$ 50	34.9 - (37.1)	22.3- (25.8)	30.6 - (34.2)
Age $\leq$ 35	22.1 -(27.3)	15.9 -(22.3)	19.9-(25.8)
Educational Achievement			
Low	36.2 - (36.6)	23.7- (28.3)	32.1 - (34.6)
Medium	20.7 -(24.7)	17.5 -(22.5)	19.5-(23.9)
High	18.1 -(24.6)	10.5 -(13.7)	15.4-(21.7)

5.1.1 Unemployment duration and well-being: how to find the causality direction ?

Unemployment duration might affect well-being through a habituation effect. In their review of unemployment-related psychology findings, Darity and Goldsmith (1996) describe three phases of emotional response after a job loss. A first shock phase where optimism still predominates, followed by a phase of pessimism and helplessness, and finally a phase of fatalism feelings with habituation.

If individuals adapt to being jobless, we should observe a higher well-being in long-term unemployed than in those who recently lost their job. Controlling for individual effects we should observe, among the unemployed, a rise in well-being with time spent in unemployment. However, upon comparing well-being across different categories of unemployed one cannot rule out a sample selection issue - arising in pooled regressions.[15] That is why pooled regressions yield different estimates than panel data regressions. Using panel data

[15] Through a shift-share mechanism. Those who stay unemployed longer are different : those suffering the most might have left to inactivity or back to work. Those suffering less from unemployment stay jobless. A selection bias arises in cross-section

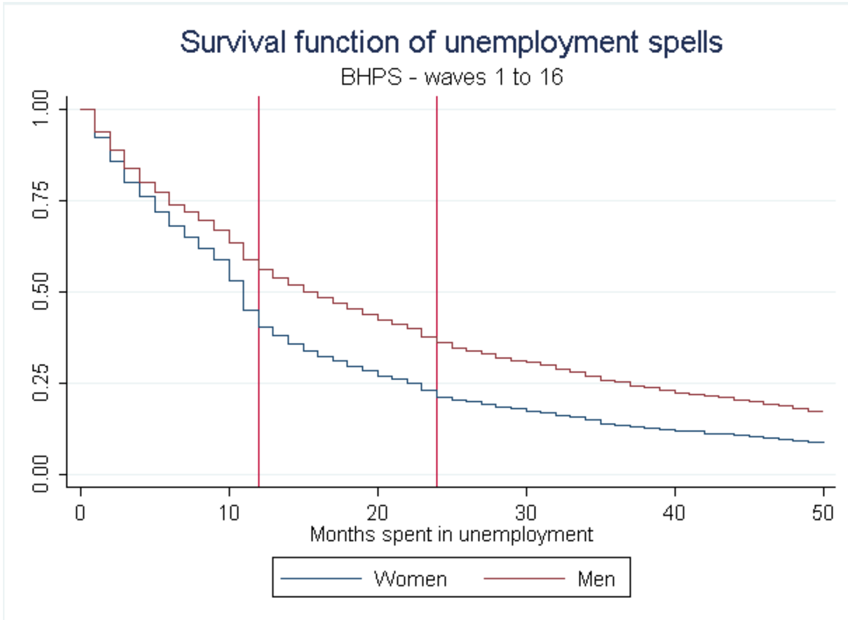

Figure 3: Survival function of unemployment spells, by gender.

(individual fixed effects) is the proper way to estimate the impact of duration on well-being. Clark (2006) does this exercise using three European panel data sets. For the pooled data, he uses an interaction term between duration and unemployment. He finds that panel data does not support the hypothesis of habituation, when using the GSOEP and the ECHP[16], but the results are not significant using the BHPS. The same exercise is executed here.

Using pooled data, the interaction term between unemployment and its duration, it is found that unemployment duration has a positive and significant effect on well-being, when one does not control for the other life variables. However, if one controls for life variables, then duration has no effect on well-being. This hints that duration is associated with the life variables mentioned above, but not directly with well-being. The transition matrix shown before provides evidence that staying in unemployment has no different effect on well-being than staying in employment. As pooled data is not rigourous, panel data specifications are used. Introducing individual fixed effects makes it possible to regress the change in well-being to the change in duration. A fixed effect logit is used to estimate this effect of duration on well-being, for the unemployed. The results show that the coefficient of duration is not significant. Hence, it can be said that the effect of unemployment on well-being is independent from its duration. These results are shown in Table 19 in the appendix, which presents both pooled and fixed-effects results.

[16]GSOEP is the German Socio-Economic Panel ; ECHP is the European Community Household Panel

5.2 The role of social norms in duration

This section tests whether or not the length of the unemployment spell is affected by the change in well-being reported when losing a job. A variable is created that calculates the reported drop in happiness when the individual enters unemployment. This variable is named "Difference in happiness". It stands for $V_e - V_u$, which in the job search theory literature is the utility difference between being employed (V_e), and unemployed, (V_u). Even though information on 5700 unemployment spells are available, there are only 1400 observations for the reported changes in well-being. This is due to the fact that data for SWB is yearly, whereas the unemployment spells are coded monthly. This variable created has exactly the same distribution of values as the variable created in the transition matrix. It shows the difference in GHQ that an individual self-reports when he/she loses its job. The distribution of this variable is presented in Figure 4, which has to be read as follows : 10% of the individuals report a drop of -1 in well-being when losing their job. 31% report feeling no change in their well-being. As it is observable, a significant proportion of the individuals record feeling *happier* when losing a job (almost 18%). The majority, however, reports feeling worse off (42%). the average *loss* of well-being is equal to 1, on a 12 points scale. This is a considerable drop, given that SWB is highly skewed to the top.

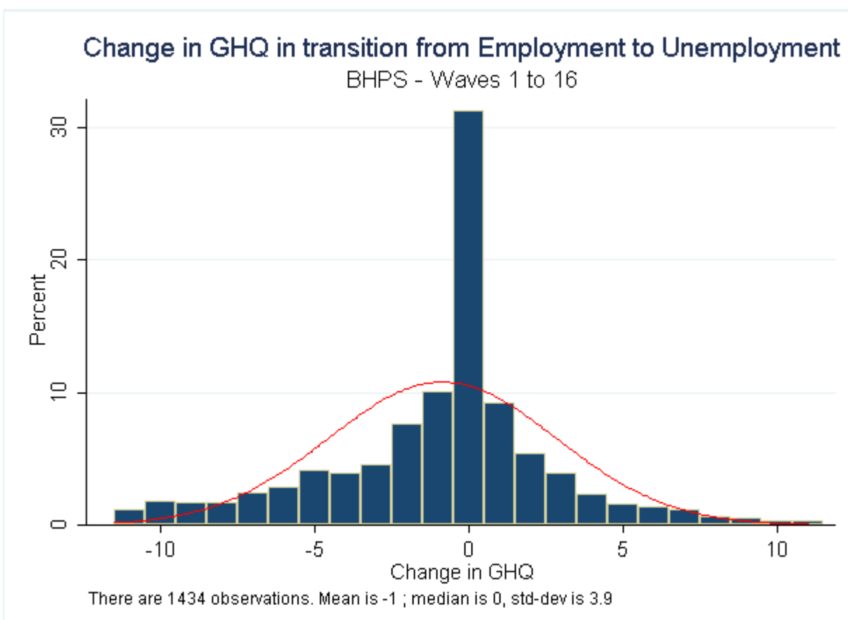

Figure 4: Change in GHQ following exit from employment

Those 1400 observations are used to run two duration models. The first uses standard OLS while the second is a proportional hazard model. The proportional hazard estimation method used is a Cox model, the standard for duration analysis. In both models the duration of unemployment is explained by a list of controls plus the drop in well-being associated with being jobless. The results from these estimations are presented in Table 7 and Table 8, and all the details about the modelling of duration and the significance of the coefficients are explained in section 7.2 of the appendix. The coefficient for the change in SWB is negative and significant. Since the change in well-being is negative, it suggest that the more an individual says it suffers from losing a job, the quicker he returns to work. The results of both estimations are presented in the Table 7.

The results from the OLS regression are in line with the Cox duration model. The coefficients *difference in happiness* are positive and significant at the 1% level in both the OLS and Cox regressions. Furthermore, the coefficients are not affected by the inclusion of demographic controls, as shown in specifications (2) and (4). It suggest that the relationship between the drop in happiness and the duration of unemployment is independent from these controls. The results read as follows: a one point increase in happiness (when losing a job) is associated with a 0.25 months increase in unemployment duration, even after controlling for other factors. Both models suggest a negative relationship between duration in unemployment and "hapiness drop". The larger $V_e - V_u$ (the happiness drop an individual reports between being employed and unemployed), the shorter his unemployment duration will be.

The regional jobless rate is also likely to affect time spent looking for work: if more people compete to get jobs, average search duration should increase. As shown in the empirical literature, unemployment benefits should also increase duration, because they have an effect on the reservation wage. We also add a dummy for unemployed spouse. Finally, two different measures of well-being are tested. First, I add the coeffcient "difference in happiness". Second, I create a dummy when the initial drop in well-being is larger than 1, and call it *bigloss*. The results are in Table 8.

As in the previous table, the OLS results in specifications (1) to (4) are similar to the StCox duration model in specifications (5) to (8). Women, the young and the highly educated spend less time in unemployment. When more people are jobless in one's region, duration increases. Unemployment Benefits also push individuals to keep looking for a job longer (their reservation wage is higher). Specifications (4) and (8) are the most complete ones, and they show that the coefficient for "difference in happiness" is positive and significant at the 1% level. Since the change in well-being is negative, it suggests that the more an individual says it suffers from losing a job, the quicker he returns to work. Column 3 confirms this intuition: those who suffered a big loss in well-being when losing their job are spending less time in unemployment. The results suggest that a one point increase in happiness (when losing a job) is associated with a 0.3 months increase in unemployment duration, even after controlling for other factors.

Finally, having an unemployed spouse increases one's unemployment duration, possibly due to the comparison effect presented earlier. The proportional hazard model confirms the OLS results. Those who suffered a big loss have a higher hazard rate, while the diff-hap coefficient is negative : the less one is hurt by unemployment, the lower the hazard rate out of unemployment.

Table 7: Dependent variable: duration of unemployment

	(1) Cox	(2) Cox	(3) OLS	(4) OLS
GHQ change	-0.0261***	-0.0268***	0.246***	0.270***
	(0.00712)	(0.00711)	(0.0692)	(0.0687)
Age		-0.0402**		0.443**
		(0.0176)		(0.172)
Age sq.		0.000456**		-0.00488**
		(0.000218)		(0.00213)
Gender		-0.290***		2.910***
		(0.0572)		(0.557)
Educ. Low		-0.311***		3.443***
		(0.0694)		(0.675)
Educ. Medium		-0.122*		1.350**
		(0.0681)		(0.666)
Region dummies	No	Yes	No	Yes
Constant		Yes	Yes	Yes
Observations	1342	1325	1436	1416
R-squared			0.009	0.051

5.2.1 Social norms and duration : empirical evidence from the duration model

Another piece of evidence suggesting that those who suffer more from the job loss return to work quicker is provided in the Figure 5, in which a Kaplan-Meier survival function is estimated for two different populations. The unemployment spells are split in 2 different sub-samples: those for whom the GHQ loss is high (drop of 2 or more in well-being) are grouped together in the high-loss sample. Those for whom the loss is low (no change or increase in well-being) are grouped in the low-loss group. Then, a Kaplan-Meier survival function is estimated for each sub-sample. The idea here is to provide visual evidence to see if those who suffer from losing their job leave unemployment more rapidly than the others. The results are shown in Figure 5. The graph shows 2 lines. The blue line (above) estimates the return to work for those who suffered *less* from the job loss. The red line

Table 8: Dependent variable : duration in unemployment, measured in months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ols	ols	ols	ols	stcox	stcox	stcox	stcox
Age	0.487**	0.114	0.319	0.337	-0.0257***	-0.00759	-0.0296	-0.0314
	(0.209)	(0.317)	(0.221)	(0.221)	(0.00791)	(0.0116)	(0.0248)	(0.0248)
Age sq.	-0.00270	1.14e-06	-0.00340	-0.00359	0.000193*	4.38e-05	0.000331	0.000350
	(0.00263)	(0.00387)	(0.00263)	(0.00263)	(9.95e-05)	(0.000141)	(0.000296)	(0.000296)
Male	7.897***	6.016***	1.851***	1.951***	-0.309***	-0.267***	-0.228***	-0.238***
	(0.770)	(1.168)	(0.667)	(0.667)	(0.0287)	(0.0425)	(0.0758)	(0.0758)
Educ. Medium	-9.664***	-8.614***	-1.469*	-1.508*	0.333***	0.287***	0.154*	0.158*
	(0.890)	(1.244)	(0.783)	(0.782)	(0.0331)	(0.0451)	(0.0874)	(0.0873)
Educ. High	-13.43***	-11.14***	-2.288***	-2.327***	0.548***	0.481***	0.216**	0.226**
	(0.922)	(1.349)	(0.804)	(0.804)	(0.0344)	(0.0489)	(0.0905)	(0.0905)
Reg. Un	1.142***	1.080***	0.453***	0.456***	-0.0463***	-0.0458***	-0.0401***	-0.0405***
	(0.143)	(0.203)	(0.119)	(0.118)	(0.00538)	(0.00750)	(0.0136)	(0.0136)
Ben.Inc.	0.0110***	0.0153***	0.00566***	0.00565***	-0.000716***	-0.000479***	-0.000464**	-0.000465**
	(0.00109)	(0.00209)	(0.00153)	(0.00153)	(5.83e-05)	(7.93e-05)	(0.000191)	(0.000192)
Sp.Unmp		9.156***	1.396**	1.465**		-0.355***	-0.189**	-0.188**
		(1.166)	(0.708)	(0.708)		(0.0424)	(0.0810)	(0.0809)
Bigloss			-2.275***				0.225***	
			(0.630)				(0.0717)	
Diff-hap				0.298***				-0.0309***
				(0.0802)				(0.00898)
Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes				
Observations	5725	3030	885	885	5501	2909	824	824
R-squared	0.122	0.146	0.092	0.093				

Source: BHPS, waves 1-16, pooled data. Absolute value of t stat in parentheses. * significant at 5%; **, at 1%. The reference category for education is low educational achievement.

Bigloss is a dummy = 1 when an individual reports a loss of happiness larger than 1 point when losing his job.

Diff-hap measures the initial change in happiness when becoming unemployed. Given that most observations of Diff-hap are negative, the results have to be interpreted as follows: if happier about losing a job, then one spends more time in unemployment.

(below) estimates the rate for those for suffered *more*. For the least happy, the rate of return to work is higher (red line) than for those who suffer less (blue line), thus confirming (visually) that those who report feeling worse at the moment of losing their job are quicker in leaving unemployment.

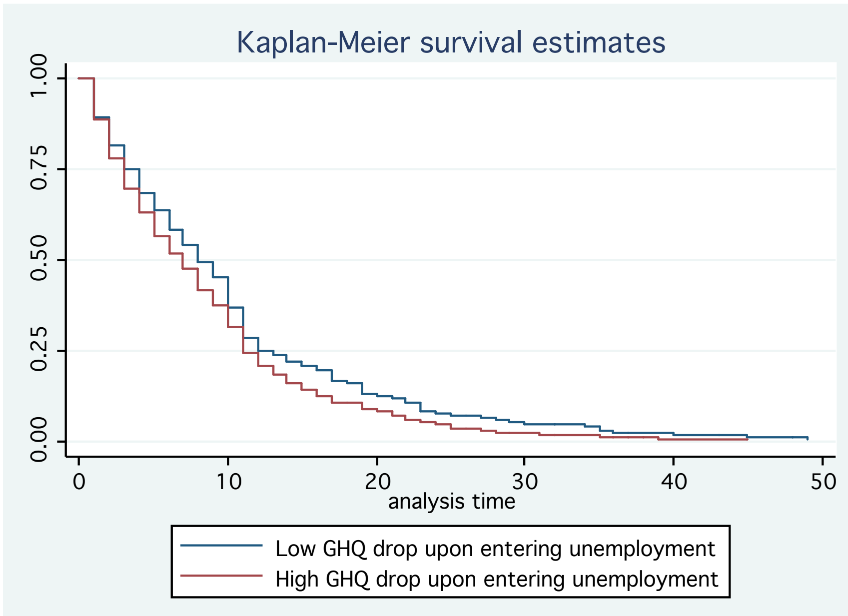

Figure 5: Survival in unemployment for those "suffering" and those "not suffering" when leaving employment

The difference in both survival functions is significant at the 80% level from the 5th month onwards. Hence, this figure provides some visual evidence that the rate of return to work is lower for individuals who report being less hurt from unemployment[17]. In the next subsection, it is shown that the channel through which their return rate is lower could be their search effort.

5.3 Is search intensity related to change in GHQ ?

The BHPS has a section designed in a similar way to the LFS (Labor Force Survey), intended to measure unemployment by the ILO standards. In this section, unemployed

[17]This result also confirms the prediction of Clark and Lucas (2006) that sample selection bias arises if one uses pooled data OLS regressions to estimate the impact of unemployment duration on well-being. It seems that those feeling worse leave unemployment sooner than the others

persons are being asked if they have been searching for a job in the last week, and/or in the last month, their response being limited to Yes/No. Their answer can provide some information on the search intensity of the group as a whole. Using the previous sample of GHQ differences, two groups are created. The first group consists of those who report a large utility loss (higher than 1 point of SWB) when they lose their job. The second group consists of those who report either no utility change or are happier being unemployed.

Table 9 shows the average search intensity for the two groups. Comparing the means, search intensity is slightly different between the two groups: 62% of the group suffering from being unemployed searched for work last week, whereas this drops to 55% for the others. These results suggest that those being hurt by the job loss search more intensively than those who do not report a fall in SWB [18]. A means test (not reported) confirms that both means are different at 99%. A probit of "search last week" is presented in Table 10, in which the same controls as for duration are used. The dummy *bigloss* is significant at the 5% level, even after controlling for all sorts of individual, household and regional characteristics in specifications (1) to (4).

Table 9: Search intensity: population means

Group	Mean	Std. Err.	N.Obs
"High GHQ drop"	0.625	.021	554
"No GHQ drop"	0.55	.028	324

Answers to the question: "Have you looked for any kind of paid job in the last week?"

[18] The reverse causality (search causing unhappiness) is avoided here because we are using the *initial* drop in happiness, which is measured only once and is time-invariant.

Table 10: Dependent variable: Have you looked for any kind of paid job last week?

	(1) search	(2) search	(3) search	(4) search
bigloss	0.0611**	0.0592**	0.0582**	0.0579**
	(0.0284)	(0.0286)	(0.0286)	(0.0287)
age	-0.00337***	-0.00356**	-0.00365**	-0.00373**
	(0.00123)	(0.00156)	(0.00156)	(0.00157)
sex	0.189***	0.189***	0.192***	0.193***
	(0.0289)	(0.0293)	(0.0294)	(0.0295)
educ2	0.0833**	0.0836**	0.0766**	0.0744**
	(0.0339)	(0.0340)	(0.0343)	(0.0345)
educ3	0.0722**	0.0749**	0.0754**	0.0744**
	(0.0343)	(0.0344)	(0.0345)	(0.0346)
Observations	1238	1238	1235	1235
Household controls	No	Yes	Yes	Yes
Region dummies	No	No	Yes	Yes
Unemployment rate	No	No	No	Yes

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Household controls are marital status and household size

5.4 Conclusion on unemployment duration

The length of time an individual spends being unemployed depends on numerous factors and affects an equally large number of outcomes. Gender and age can be thought of exogenous but one cannot distinguish between supply or demand factors through which they affect the rate of return to work. Is it that the women and the young are better at looking for jobs, more motivated (supply side), or is it that demand for them is higher ?

The interrelation between SWB and search intensity provides -at last - a pure labor supply story. Upon losing their job, people self-report a drop in their subjective well-being. This drop depends on how many other around are unemployed, and it also affects their search behaviour. When those around are jobless, being unemployed hurts less and job search effort is less intensive. Hence, the rate of return to work is also lower. These results suggest that the job search intensity and the rate of return to work are both dependent on the difference of well being between being employed and unemployed. In standard models of job search, the intensity of search is also derived from the utility differences from the two states. However, in those models, utility is only determined by the differences in the flow of income. The results presented here suggest that comparison effects play a significant role in the rate of return to work.

6 Conclusion

Clark (2003) found that the higher the unemployment rate among an individuals' reference group, the less that individual reported being hurt by unemployment, which was called the "social norm effect". In this paper, we provide more evidence of the "social norm effect". We show that albeit the comparison effect is strong, it differs by gender. Women suffer more than men when their spouse is made redundant. But men compare more, both to their spouses and to their regional peers. When men they lose their job, they suffer, but they suffer less if their spouse is also unemployed.

This paper goes one step further. It provides evidence that the duration of unemployment is affected by this "social norm". It is suggested here that job search behaviour is also dependent on the social norm, on the individual's perception of how socially stigmatising is unemployment.

The lesson to be drawn by these findings is that one's employment decisions have a strong externality on other's labor supply and job search effort, through comparison effects. Upon losing a job, if a relevant other is also jobless then both individuals search with less intensity. In the opposite scenario, if all relevant others are employed, search intensity increases for the unemployed. It suggest that participation to the labor market should be seen as a binary model with externalities: one's decision affects the others. As in Neumark and Postlewaite (1998) this mechanism helps in explaining the rise in women's participation rates in the 20th century, and complements the standard model of labor supply. It also explains why in high unemployment regions the jobless rate might remain higher than in low regions, or why it may take longer to fall.

Explanations of unemployment hysteresis have been so far centred around labor demand. The present findings suggest unemployment hysteresis might also come from the labor supply behaviour. If others are unemployed, I will search less and extend my unemployment duration, in turn affecting other's search and return to work. Many policy implications arise. One concerns the responses to exogenous macroeconomic shocks. Following a labor demand shock, as unemployment rises, the labor supply might also fall (shift to the left) through a comparison effect. It suggest that a policy response should correct for this externality in times of high unemployment. Future empirical research should examine in more detail the link between search intensity and the social norm effect. Future theoretical research should assess what policy responses arise now that we know how one's participation affects the others.

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7 Appendix

7.1 Is the GHQ-12 a good measure of Well-Being?

As presented by Argyle, the 12-item version of the GHQ is a good test for the following reasons. First, it has internal coherence. The 12 item correlate with each other : the Cronbach alpha is high. Second, the scores are stable over time but sensible to changes when the individual reports going through current hassles. Third, the score is correlated to reports by others who know the subject, and also to daily reports of moods, to cognitive measures and to reports from qualitative interviews. Fourth, the "immediate mood bias" is not likely to affect GHQ because the questionnaire asks questions related to the past weeks. Positivity bias is present in all types of surveys. Everyone is overconfident - except chronic depressives. Fifth, scales are comparable across individuals. The 12 questions used to build the GHQ-12 are as follow :

1. Have you recently been able to concentrate on whatever you are doing?
2. Have you recently lost much sleep over worry?
3. Have you recently felt constantly under strain ?
4. Have you recently felt you could not overcome your difficulties ?
5. Have you recently been feeling unhappy or depressed?
6. Have you recently been losing confidence in yourself ?
7. Have you recently been thinking of yourself as a worthless person?
8. Have you recently been able to enjoy your normal day-to-day activities ?
9. Have you recently been able to face up to problems?
10. Have you recently been feeling reasonably happy, all things considered ?
11. Have you recently felt capable of making decisions about things?
12. Have you recently felt that you were playing a useful part in things ?

For question 1, the responses are :
Better than usual (1) ; Same as usual (2) ; Less than usual (3) ; Much less than usual (4)
For questions, 2 to 7, the responses are :
Not at all (1) No more than usual (2) ; Rather more than usual (3) ; Much more than usual (4).
For questions 8 to 12, the responses are : More so than usual (1) About same as usual (2) Less so than usual (3) Much less than usual (4)

7.2 Duration model

This appendix provides some explanations for the duration model of unemployment. Each unemployment spell T is calculated in months. In terms of duration modelling, the length of each episode is the **survival time** in unemployment. We call the time of transition out of unemployment t, that is the **failure time** (it is the moment at which the event fails). The cumulative distribution of T is $F(t)$, and the density function is the derivative of the cumulative function with respect to time : $f(t) = \frac{dF(t)}{dt}$.
The distribution of this variable T is given in the table 10.xx . For simplicity reasons, I truncate the distribution at $T = 100$, as we are not interested in outliers. The distribution of this variable T is given by the equation :

$$F(t) = P(T \leq t)$$

This distribution $F(t)$ measures the probability of survival up to the time t. T should be seen as a continuous variable. As such, it is the first derivative of the distribution function.

The **survival function** $S(t)$ denotes the probability that the spell T continues after t or longer. For example, taking the whole sample of spells, the probability of surviving 13 months in the unemployment state is of .5 or 50%.

$$S(t) = P(T > t) = 1 - F(t)$$

Another example for the survival function : the probability of surviving 5 months in unemployment is 75% It is equal to the spells that are left, or to 1 minus proportion of spells that ended before time t.

Duration models are not always needed. We can always regress duration on other control variables, or estimate the conditional probability of an event with a binomial regression. Duration modelling is needed when we need to go beyond. If we are interested in knowing the probability of being unemployed for another month given that we were unemployed 10 months, then we need survival analysis, as this information does not come in a plain regression. Also, if we need to know the conditional probability that an ongoing spell will end, controlling for other variables, then we need survival analysis.

The **Hazard function** or the **failure rate** $\lambda(t)$ measures the death rate *given* survival until time t. Example : the failure rate between the months 12 and 23 is 50%. It means : conditional on making it to the $12th$ month, there is a 50% chance that the spell will end before the $24th$ month. It is measured as follows:

$$\lambda(t) = \lim_{\delta \to 0} \frac{P(t \leq T \leq t + \delta | T \geq t)}{\delta}$$

The cumulative hazard function is something very similar. It measures the probability of surviving over a time span [t, t+d] and it is found by integrating the hazard function over that time span.

$$\Lambda(t) = \int_0^t \lambda(x) d(x)$$

When integrating the cumulative hazard at a given point, we obtain the survival function: $S(t) = e^{-\int_0^t \lambda(x)d(x)}$

7.2.1 Cox Proportional Hazard

Above we explain the basics of duration models, but we are now interested in understanding the duration conditional on other variables. The Cox proportional hazard allows to condition duration. Stata provides a command (stcox) to run a cox proportional hazard. It estimates following proportional hazard :

$$\lambda_i(t) = e^{x_i \beta} . \lambda_0(t)$$

Where x_i stands for the value of variables affecting duration, and β is their coefficient. $\lambda_i(t)$ is the hazard rate of individual i, and λ_0 stands for the baseline hazard.

In the regression result from section 6, the proportional hazard ratio β associated with the happiness difference is equal to $0,97$. It means that the effect of a one point increase in happiness when losing a job is associated with a 2.3 months increase in unemployment duration.

7.3 A note on the use of pooled data vs fixed effect

7.3.1 Pooled data

The standard specification for an OLS estimation of well-being using panel data is the following :

$$Y_{it} = \beta_1 + \sum_{j=2}^{k} \beta_j X_{jit} + \sum_{p=1}^{s} \gamma_p Z_{pi} + \delta t + \epsilon_{it}$$

Where Y_{it} is the dependent variable (here the GHQ-12) for individual i in time t. X_j are the observed explanatory variables (employment, age, gender, civic status, etc.). Z_{pi} are the unobserved variables affecting subjective well-being, and they are the ones responsible for the unobserved heterogeneity and for creating the noise. ϵ_{it} is the disturbance term and t is added to control for a change in the intercept over time.

Assuming that Z_{pi}, the unobserved explanatory variables, do not change over time, the equation above can be rewritten as :

$$Y_{it} = \beta_1 + \sum_{j=2}^{k} \beta_j X_{jit} + \alpha_i + \delta t + \epsilon_{it}$$

where $\alpha_i = \sum_{p=1}^{s} \gamma_p Z_{pi}$; and α_i stands for the unobserved effect of all Z on Y_i. It measures the individuals' specific unobserved fixed effect. This unobserved, individual-specific fixed effect can be dropped if it is not significant. This could be done if all relevant characteristics affecting GHQ are captured by the controls X. If this is the case, then the α_{ij} term can be dropped and the data set can be used as a **pooled data set**, in which all observations from the different years are used in the same sample. The present paper presents the pooled data results before presenting the next step, the panel data results.

7.3.2 Fixed effects regressions : individual fixed-effects

Well-being levels reported by one person can be thought of being subjectively different that those reported by another person. If one cannot compare a well-being of 10 between two individuals, then we might want to control for individual fixed effects, as we are interested in understanding how *changes* in explanatory variables relate to *changes* in well-being. To do so, we must subtract the mean values of all variables (of individual i) to each observation. The mean variables are found by the equation below :

$$\bar{Y_i} = \beta_1 + \sum_{j=2}^{k} \beta_j \bar{X_{ji}} + \alpha_i + \delta\bar{t} + \bar{\epsilon_i}$$

Where $\bar{Y_i}$ accounts for the mean happiness of individual i during the years surveyed. When subtracting the individual's mean observation to their yearly observation, we obtain an equation in which the unobserved individual fixed effect α_i disappears, as also does the intercept β_1. The regression controlling for individual fixed effects is shown below :

$$Y_{it} - \bar{Y_i} = \sum_{j=2}^{k} \beta_j (X_{jit} - \bar{X_{ji}}) + \delta(t - \bar{t}) + \epsilon_{it} - \bar{\epsilon_i}$$

This within-group regression measures how the variation in observable explanatory variables affects the variation in happiness.

Three main problems arise when using individual fixed effects. First, the intercept and any explanatory variable reporting no change during the time of the survey is dropped. Since we are measuring how change in variables explain change in happiness, then gender, educational achievement and civic status will not be taken into account unless they change : their value will be zero. Second, the variation of explanatory variables within-individuals is much smaller than the variation across them. The model will have large disturbance terms and low precision in the estimates. Third, and most important, using individual fixed effect means we are controlling for *every* single individual. This leads to the loss of many degrees of freedom (as many as individuals). It significantly reduces the precision of the coefficients.

7.4 Summary statistics and regressions

Table 11: Summary statistics

Variable	Mean	Std. Dev.	N
Number of Households			
In the whole survey		.	9897
In restricted sample		.	7562
Number of Observations			
In the whole survey	199,322	.	
In restricted sample	151,567	.	
Male	0.462	0.499	151567
Age	40.926	12.586	151567
Married	0.594	0.491	151376
Separated	0.025	0.157	151376
Divorced	0.093	0.29	151376
Widowed	0.022	0.148	151376
Never Married	0.264	0.441	151376
Health Excellent	0.251	0.433	151505
Health Good	0.48	0.5	151505
Health Poor	0.27	0.444	151505
Educational Achievement : Other	0.279	0.449	149779
Educational Achievement : High	0.391	0.488	149779
Educational Achievement : Medium	0.33	0.47	149779
Employment Status, in % of the sample			
Self employed	8.56	.	12968
In paid employ	62.50	.	94700
Unemployed	4.41	.	6688
Retired	6.52	.	9881
Family care	1.07	.	1617
Student	8.60	.	13033
Long term sick/disabled	2.75	.	4164
On maternity leave	5.04	.	7641
Govt trng scheme	0.13	.	200
Something else	0.42	.	635

This table presents some descriptive statistics. There are almost 10.000 households in the 16 waves, but the restriction of the sample to the working age population reduces it to 7562.

Civic status dummies are Married, Separated, Widowed, Divorced and Never Married. Health dummies are Excellent, Good and Poor. The bottom part of the table shows the number of self-employed, employed and unemployed individuals.

Table 12: Distribution of GHQ-12

GHQ-12	Frequency	Pct	Cumulative Pct.
0	2,594	1.76	1.76
1	2,093	1.42	3.17
2	2,199	1.49	4.66
3	2,426	1.64	6.30
4	2,779	1.88	8.18
5	3,357	2.27	10.45
6	3,956	2.68	13.13
7	4,992	3.38	16.51
8	6,160	4.17	20.68
9	8,264	5.59	26.27
10	11,843	8.01	34.28
11	20,026	13.55	47.83
12	77,097	52.17	100.00

Source: BHPS. Waves 1-16.

Table 14: OLS regression of regional unemployment rate on difference in GHQ in region

Variable	Coefficient	(Std. Err.)
urate	-7.898**	(2.452)
Intercept	1.741**	(0.166)
N	302	
R^2	0.033	
$F_{(1,300)}$	10.377	

Table 13: Determinants of GHQ-12. OLS. Pooled data.

	Simple	Some Controls	Broad
Self-Employed	0,091	-0,099	-0,091
	(3.44)**	(3.77)**	(3.44)**
Unemployed	-1,247	-1,145	-1,138
	(34.74)**	(31.80)**	(31.53)**
Annual Income in 'k		0	0
		-1,82	(2.39)*
Male		0,521	0,525
		(30.58)**	(30.61)**
Age		-0,064	-0,063
		(11.41)**	(10.67)**
Age Sq. /100		0,865	0,833
		(12.97)**	(11.77)**
Married		0,059	0,074
		(2.54)*	(2.93)**
Separated		-0,9	-0,914
		(16.55)**	(16.65)**
Divorced		-0,199	-0,175
		(5.76)**	(4.96)**
Widowed		-0,483	-0,462
		(6.34)**	(6.03)**
Health Good		-0,457	-0,451
		(23.87)**	(23.40)**
Health Poor		-1,883	-1,878
		(79.68)**	(79.11)**
Education High		-0,374	-0,387
		(16.75)**	(17.05)**
Education Medium		-0,194	-0,205
		(8.47)**	(8.91)**
Children Dummies	No	No	Yes
Wave Dummies	No	No	Yes
Regional Dummies	No	No	Yes
Constant	10,345	12,055	11,884
	(1127.55)**	(111.53)**	(86.49)**
Observations	111837	110211	109461
R-squared	0,01	0,09	0,09

Source: BHPS, waves 1-16, pooled data. Absolute value of T statistics in parentheses. * significant at 5%; * * significant at 1%

Reference dummy for labor market status is "Paid Employmen"t ; for civic status is "Never Married" ; for health is "Poor" and for Education "Low".

Table 15: Transition Matrix - Change in Labor and in Well-Being in Men

	Labor Status in t		
Labor Force Status in t-1	Employed	Unemployed	Self-Employed
Employed			
Mean	-0,04	-1,15	0,02
s-e	0,01	0,12	0,08
N	34 355	833	956
Unemployed			
Mean	1,59	-0,05	1,19
s-e	0,12	0,09	0,25
N	938	1 444	195
Self-Employed			
Mean	0,129	-0,941	-0,031
s-e	0,10	0,32	0,03
N	852	136	6262

Table 16: Transition Matrix - Change in Labor and in Well-Being in Women

	Labor Status in t		
Labor Force Status in t-1	Employed	Unemployed	Self-Employed
Employed			
Mean	-0,06	-0,99	0,03
s-e	0,02	0,18	0,14
N	35 820	586	530
Unemployed			
Mean	1,15	0,10	1,23
s-e	0,15	0,18	0,67
N	614	484	44
Self-Employed			
Mean	0,40	-0,81	-0,06
s-e	0,16	0,58	0,07
N	447	48	2139

The transition matrix above shows how GHQ changes following a transition between labor states.

Table 17: Dependent variable: GHQ12. OLS - Pooled Data.

	Simple	Spouse Employment	Regional Employment	Broad
Self-Employed	-0,1	-0,098	-0,1	-0,097
	(3.55)**	(3.46)**	(3.52)**	(3.44)**
Unemployed	-1,167	-1,549	-1,675	-1,947
	(17.66)**	(18.10)**	(10.75)**	(12.17)**
Reg.Unmpl	0,003	0,003	-0,001	-0,001
	-0,39	-0,39	-0,21	-0,11
Spouse Employed=1	0,1	0,157	0,102	0,156
	(4.18)**	(6.23)**	(4.24)**	(6.19)**
Reg.Unmpl.* Unmpl.			0,075	0,061
			(3.59)**	(2.89)**
Spouse.Unmpl*Unmpl		0,787		0,757
		(6.49)**		(6.20)**
Male	0,515	0,514	0,514	0,513
	(26.92)**	(26.84)**	(26.88)**	(26.81)**
Age	-0,076	-0,076	-0,076	-0,076
	(9.81)**	(9.75)**	(9.77)**	(9.72)**
Age/100	0,952	0,949	0,949	0,946
	(10.65)**	(10.63)**	(10.61)**	(10.59)**
Health : Good	-0,446	-0,446	-0,446	-0,446
	(25.63)**	(25.66)**	(25.62)**	(25.65)**
Health : Poor	-1,816	-1,818	-1,816	-1,818
	(56.94)**	(56.91)**	(56.97)**	(56.94)**
Education : High	-0,449	-0,443	-0,449	-0,443
	(18.66)**	(18.39)**	(18.67)**	(18.41)**
Education : Medium	-0,257	-0,252	-0,256	-0,252
	(10.99)**	(10.76)**	(10.97)**	(10.75)**
Marital dummies	Yes	Yes	Yes	Yes
Income in 'k	Yes	Yes	Yes	Yes
Children Dummies	Yes	Yes	Yes	Yes
Wave Dummies	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Observations	80850	80850	80850	80850
R-squared	0,08	0,08	0,08	0,08

Source: BHPS, waves 1-16, pooled data. Absolute value of T statistics in parentheses. * significant at 5%; * * significant at 1%

Reference dummy for labor market status is "Paid Employmen"t ; for civic status is "Never Married" ; for health is "Poor" and for Education "Low".

Table 19: Test of habituation hypothesis

	(1)	(2)	(3)	(4)	(5)	(6)
	all	men	women	all	men	women
unemployment duration	-0,013	0,012	0,009	0,006	0,006	0,011
	(7,71)*	(-6,55)	(-2,47)	(-1,66)	(-1,44)	(-0,96)
Fixed-Effects	No	No	No	Yes	Yes	Yes
constant	8,8	9,1	8,5	8,9	9,2	8,4
Observations	5498	3547	1951	5498	3547	1951

Table 18: Dependent Variable: GHQ12. OLS with Fixed Effects

	All	Men	Women	All	Men	Women	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Self-Emp	-0,05	-0,114	0,073	-0,081	-0,147	0,033	-0,081	-0,146	0,035	-0,078	-0,145	0,034
	-1,19	(2.46)*	-0,92	-1,67	(2.64)**	-0,35	-1,68	(2.63)**	-0,38	-1,6	(2.60)**	-0,36
Unemp.	-1,234	-1,276	-1,177	-1,261	-1,427	-0,977	-1,114	-1,542	-0,48	-1,44	-1,79	-1,006
	(27.0)**	(24.1)**	(14.8)**	(15.8)**	(14.5)**	(7.1)**	(5.7)**	(6.8)**	-1,3	(14.4)**	(13.7)**	(6.6)**
Reg.U.				-0,003	0,001	-0,007	-0,002	0	-0,005	-0,003	0,001	-0,007
				-0,4	-0,14	-0,64	-0,26	-0,03	-0,46	-0,42	-0,09	-0,64
Sp. Emp				0,156	0,034	0,406	0,155	0,035	0,403	0,185	0,079	0,415
				(4.33)**	-0,86	(5.35)**	(4.31)**	-0,87	(5.31)**	(5.10)**	(1.97)*	(5.41)**
Sp. U.*U										0,496	0,801	0,139
										(3.36)**	(4.69)**	-0,44
Reg.U*U							-0,022	0,017	-0,08			
							-0,84	-0,59	-1,43			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	111837	58195	53642	80850	42746	38104	80850	42746	38104	80850	42746	38104
R-sq.	0,43	0,44	0,42	0,45	0,45	0,44	0,45	0,45	0,44	0,45	0,45	0,44