Feeling Useless: The Effect of Unemployment on Mental Health in the Great Recession*

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Abstract

This article documents a strong connection between unemployment and mental disorders using data from the Spanish National Health Survey. We exploit the collapse of the construction sector to identify the causal effect of job loss. Our results suggest that an increase of the unemployment rate by 10 percent due to the breakdown in construction raised mental disorders in the affected population by 3 percent. We argue that the large size of this effect responds to the fact that the construction sector was at the centre of the economic recession. As a result, workers exposed to the negative labor demand shock faced very low chances of re-entering employment. We show that this led to long unemployment spells, stress, hopelessness and feelings of uselessness.

JEL Codes: I10, J60, C26

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1 Introduction

The Great Economic Recession which started with a global financial crisis in 2007 had severe effects on the Spanish labor market. In particular, the unemployment rate followed a dramatic path, going from about 8 percent in 2007 to more than 25 percent in 2011. The construction sector was hit the hardest: more than 60 percent of all jobs in this sector were lost by 2013.[1] As a result, between 2007 and 2013 employment in the sector decreased from 13 percent of total employment to less than 6 percent.

This article shows that the unemployment spells suffered by the affected groups led to a drastic relative deterioration of their mental health. Figure 1 presents measures of mental well-being by employment status taken from the Spanish National Health Surveys of 2006 and 2011. Unemployed workers are clearly in worse health than their employed counterparts. They are less self-confident, appear overwhelmed by their problems and report markedly higher diagnosed mental disorders. However, these correlations come from cross-sectional evidence and are, therefore, uninformative about the underlying direction of causality. That is, mental disorders such as depression or chronic anxiety could be the result of unemployment, but it could also be that poor mental health leads to job loss or the inability to find new employment.

The Spanish economic recession offers a unique setting to study the causal relationship between unemployment and health. First, the deterioration of employment opportunities was directly linked to workers' exposure to the construction sector. Since the burst of the real estate bubble at the end of 2007, 3.6 million jobs have been lost: almost half of them in construction.[2] Second, the high concentration of job destruction in this sector, where workers with little education had been attracted by a decade of expansion, made unemployment a very hard trap to escape. Hence, the negative labor demand shock resulting from the collapse of the housing market resulted in job losses followed by a very low re-employment probability for the most affected workers - unskilled young workers in construction (ILO 2014). We show that long-term unemployment in this group increased dramatically and argue that the nature of this economic episode allows us to identify the effect of unemployment on health net of the biases resulting from the non-random selection of workers in and out of unemployment.

[1] See Figure A1 in the appendix.

[2] Total employment was 20,356,000 in 2007 and 16,750,000 in 2013. Employment in construction was 2,697,300 in 2007 and 1,016,200 in 2013 (Source: Spanish Labor Force Survey, several years).

Our identification strategy follows that in Bartik (1991) and Blanchard and Katz (1992) where the regional composition of the economy (or the importance of the construction sector) at an initial period (i.e. pre-crisis years) is used to predict exogenous changes in employment over time. The IV estimates suggest an important negative effect of unemployment on mental health, while non-robust findings appear on other health outcomes, including death rates. We also find that the IV estimates are much larger than those suggested by Figure 1 or the OLS regressions.[3] These findings support the view that the relative deterioration of mental health in the crisis was indeed driven by the absence of jobs in a specific labor market. In this view laid-off workers from construction got trapped in long-term unemployment by drastic shifts in the demand for labor. This affected their mental health through stress and a feeling of uselessness and helplessness.

In the following section we review the related literature. Section 3 presents evidence on the changes in unemployment and unemployment duration with a focus on the construction sector. Section 4 discusses our data sources and section 5 provides a first look at the data. Section 6 introduces the empirical model and discusses our identification strategy. Section 7 presents our estimation results and some robustness checks. This is followed by some concluding remarks.

2 Related Literature and Contribution

It is well documented that unemployment is associated with bad health outcomes (see for example Kasl and Jones 2000). However, an unresolved debate remains about the direction of causality and about why the association arises. At least three different paths can lead to the observation of a less healthy stock of unemployed compared to the employed. First, ill workers are more likely to become unemployed (Böckerman and Ilmakunnas 2009; García-Gomez et al. 2011). Second, there is evidence that poor health causes longer unemployment spells (Stewart 2001). Finally, unemployment itself can lead to a deterioration of health. We focus on the identification of this third channel.

Downsizing or firm closure has been widely used to identify the causal effect of job loss on health. Several studies document an important increase in the risk of mortality after job displacement (see Sullivan and von Wachter 2009, Eliason and Storrie 2009a and Browning and Heinesen 2012) as well as an increase in sickness benefits and disability pension utilization (Kuhn

[3] This is even true when we control for province/time fixed effects so that we identify the effect of unemployment from variation within the Spanish provinces.

et al. 2009 and Rege et al. 2009). There is also evidence that job displacement increases the risk of suicide and suicide attempts, hospitalization, mental illness and substance abuse (Eliason and Storrie 2009b, Browning and Heinesen 2012 and Black et al. 2015).

Episodes of businesses closed or downsized provide an exogenous source of variation for the unemployment entry rate as job losses are unlikely to be related to workers' health. However, the impact of unemployment on health is driven not only by the initial displacement but also by the ability of finding a new job. In other words, there may be both "occurrence" and "duration" effects of unemployment (Bjorklund 1985). Salm (2009), for instance, reports evidence that unemployment duration is associated with strongly declining health. The length of unemployment is clearly not exogenous as persons with deteriorating health may have different chances to exit unemployment. For example, Stewart (2001) finds that individuals in poor health have longer unemployment spells. Alternatively, it could also be that individuals who (expect to) suffer most from unemployment are more likely to try harder to escape it.

In this paper we employ the dramatic experience of the Spanish labor market during the last decade to assess the effect of unemployment on health. We argue that the massive destruction of jobs in the construction sector affected both the unemployment entry rate as well as its duration. Between 2007 and 2013 more than 60 percent of the jobs in construction were lost and employment in this sector decreased from 13 percent to less than 6 percent of total employment. This large episode of massive layoffs motivated by the burst of the housing bubble was clearly unrelated to the health status of workers in construction. Moreover, laid-off construction workers - mostly young and unskilled with no experience in other sectors (ILO 2014) - faced extremely adverse labor market conditions and were trapped in unemployment for long. The nature of this aggregate negative labor demand shock allows us to identify the effect of being jobless on health net of selection in and out of unemployment.

The paper focuses mainly on mental health and well-being. Existing literature suggests that the effect of unemployment can work through two channels. First, the reduction of income that accompanies job losses (Ruhm 1991, Jacobson et al. 1993 and Eliason and Storrie 2006) may force affected individuals to make important economic adjustments. Financial strain have consistently been found to be an important predictor of psychological distress among the unemployed (Kessler, Turner, and House 1987; Warr and Jackson 1984). Second, unemployment may also have important social and non-monetary consequences related to the loss of work relationships, of self-esteem, sense of control, meaning of life and time structure that may negatively affect health (Erikson 1959, Seligman 1975, Jahoda 1982 and Warr 1987). Particularly relevant for our study is the phased response in emotional well-being found by Hill (1977) and others. In the first stage of the job loss the individual is still optimistic. In the second stage, when efforts to obtain work fail, the individual becomes pessimistic and suffers active distress. In the third stage, the unemployed become fatalistic and adapts to the new state. Helplessness becomes acute among long-term unemployed.

Our paper is also related to another stream of the literature that has examined the relationship between health and aggregate economic conditions, in particular unemployment. Several authors have documented that aggregate mortality is strongly procyclical (Ruhm 2000, 2005, Miller et al. 209 and Stevens et al. 2015), but that mental health (measured by the suicide rate) deteriorates during economic downturns (Ruhm 2003). The literature on happiness and subjective well-being have also shown that higher levels of unemployment are linked to lower reported happiness (Clark and Oswald 1994, Winkelmann and Winkelmann 1998, Di Tella et al. 2001 and Stutzer and Lalive 2004). Studies with individual data also identify a positive effect of unemployment on suicide, depression, physician consultations, illness episodes and substance abuse (see among others Dooley et al. 1996, Burgard et al. 2005 and Browning and Heinesen 2012).

3 The Spanish Economic Crisis

In this section we describe the main aspects of the economic crisis in Spain. In particular, we highlight two important features that are relevant for our empirical investigation. First, the negative shock to employment opportunities was mainly concentrated in the construction sector. Second, individuals who lost their jobs faced extremely adverse labor market conditions leading to a dramatic increase in the duration of their unemployment spells.

Figure 2 shows the evolution of the average unemployment rate for provinces grouped according to the size of the construction sector in 2006 (i.e. large or small).[4] From the graph it is clear that the developments on the labor market between 2000 and 2012 were disastrous, as the unemployment rate dramatically skyrocketed over the period. Moreover, the shock was particularly severe in the group of regions with large levels of construction. Notice that until 2007 both groups were reducing unemployment almost in parallel. By 2012 unemployment in provinces with a large construction sector was almost 5 percentage points higher.

Figure 3 highlights the connection between the size of the construction sector and the inci-

[4] A province has a large construction sector if the share of employment in construction over total employment is above the mean value.

dence of unemployment. The y-axis shows the change in the unemployment rate between 2006 and 2011 in the 52 Spanish provinces. In the x-axis we show the share of employment in the construction sector over the total active population in 2006, before the crisis hit in 2007. The figure clearly shows that the largest increases in unemployment were observed in those regions where employment in construction was the highest before the crisis. Some provinces had almost 1/5 of their active population employed in construction when the housing market collapsed. Five years later unemployment had risen by a similar amount.[5] In contrast, in regions with less construction, the unemployment rate suffered a much less pronounced increase.

In addition to the dramatic increase in the number of unemployed workers, the crisis in the Spanish labor market has also been characterized by an extremely low re-entry probability after job loss. Figure 4 reports the share of short term (less than 12 months) and long term unemployment over the active population in Spain. Until the Great Recession both rates were slightly decreasing. Long term unemployment in particular decreased from over 7 percent of the active population in 2000 to under 4 percent in 2007. In 2008, short-term unemployment increased drastically by about 2.5 percentage points. The following year the short-term rate increased again by 3.5 percentage points and stabilized thereafter. Long-term unemployment remained stable in 2008 but increased by about 2.7 percentage points in 2009 and by 2.1 percentage points in 2010. The long-term rate increased in all the following years and stood at 15 percent in 2013. This meant that the vast majority of individuals that lost their work in 2008 and 2009 did not find a job afterwards.

Individual reports on unemployment duration also reveal this change in the labor market. Figure 5a shows the distribution of unemployment duration in the National Health Survey sample for the years 2006 and 2011. The duration of unemployment changed dramatically between these two years. In 2006 about half the unemployed workers experienced spells that lasted less than 6 months. As a result of the economic downturn this group increased slightly from over 5 percent of the active population in 2006 to about 7 percent in 2011. Most of the additional unemployed, however, experienced longer spells. In particular, the group with unemployment spells of more than two years more than tripled in size from about 2 percent in 2006 to almost 8 percent in 2011. Construction workers were most affected by long-term unemployment. In the

[5] For instance, in Tenerife the share of workers in the construction sector was 21% of the employed population in 2006. The unemployment rate increased from 8% to 30% in the province between 2007 and 2011.

National Health Survey individuals are asked in both 2006 and 2011 whether their current or last employment was in construction. Figure 5b shows unemployment duration in this group, again as percent of the active population. Unemployment in this group increased particularly strongly and an overwhelming majority of the additional unemployed was without employment for longer than a year in 2011. While the Spanish Labor Force Survey does not provide data on long-term unemployment by sector of last employment, it should be clear from these numbers that, if anything, the pattern of unemployment duration displayed in Figure 4 should be even more extreme for construction workers.

4 Data

Information at the individual level on health and employment status as well as other socioeconomic characteristics is obtained from different waves of the National Health Survey (Encuesta Nacional de Salud - ENS). This survey exists for different years between 1987 and 2011. In the years 1987, 1993, 1995, 1997 and 2001 the survey was conducted by the Centro de Investigaciones Sociologicas (CIS), an independent entity chosen by the Spanish Ministry of the Presidency. In 2003, 2006 and 2011 the Ministry of Health was in charge of it. Although the different waves of the survey are designed to analyze the health status and practices of the Spanish population, the questions are, in general, not comparable across time. Most part of our analysis focuses on the comparison between the year 2006 (just before the collapse of the Spanish economy) and 2011 (in the middle of the economic downturn), using the last two waves of the survey. The questions in these two surveys are almost identical. We present additional results for a general health measure in the years 2001, 2003, 2006 and 2011.[6]

We exclude individuals that are under 17 or older than 64. Unless stated otherwise we only look at the active population, which implies that we exclude students, disabled people and pensioners. Table 1 presents descriptive statistics for the variables we use from the Spanish

[6] The question regarding general health status is the same in 2001, 2003, 2006 and 2011: *"Over the last 12 months, would you say your health has been ... ? Very good, Good, Average, Poor or Very poor"*. In 2006 and 2011 the same question is asked regarding diagnosed mental disorders: *Have you ever been diagnosed by your doctor with chronic depression, anxiety or any other mental disorder?*. However, in 2001 and 2003 the question is: *Are you currently diagnosed by your doctor with chronic depression, anxiety or any other mental disorder?"* mean answers change considerably.

National Health Survey. The sample size is about 46,000 in the larger sample and almost 25,000 in the last two waves 2006 and 2011, although it varies slightly depending on the specific health question we consider.

The survey provides very detailed questions on several aspects of health. We report descriptive statistics for all these variables in Table 1. First, respondents are required to provide a self assessment of their general health status, classifying it in *very good/good/bad/very bad* health. We recode this variable giving values of 1 to reports of *very good* or *good* health and 0 otherwise. Almost 80 percent of our sample reports good or very good health: this share does not change depending on the sample, suggesting a relative stability of subjective health over time. Second, respondents are asked whether they received a diagnosis from a doctor for a set of different illnesses: chronic back pain, chronic headache, heart attack, stroke and mental disorder. Of particular interest for us is the question regarding whether the respondent has been diagnosed with a mental disorder (i.e. depression or chronic anxiety): 8.4 percent report a mental disorder diagnosis in the surveys 2006-2011. Third, a measure of self-reported mental health is obtained by asking respondents whether they suffer from some mental disorder. The share of respondents who report suffering from mental disorder (8,7 percent) is slightly larger than those reporting to have received a diagnosis for mental disorder.

Health was improving slightly between 2006 and 2011. The percentage of individuals reporting good health increased from 76 percent to 81 percent, for example. Reported mental disorders fell from 9 percent in 2006 to 7 percent in 2011.[7] However, this positive trend was not uniform. Individuals associated with the construction sector reported slightly worse mental health on average in 2011 than in 2006 (see Appendix Table A1).

In 2006 and 2011 the National Health Survey conducted a special survey of twelve questions related to mental well-being (see Panel B in Table 1). The questions are part of the General Health Questionnaire (GHQ) which was developed as a screening instrument for psychiatric illness and has recently been studied in several economics papers (see, among others, Dustmann and Fasani, forthcoming,) Responses in this survey are coded between 0 and 3, where 3 is always

[7] This is in line with data on death rates. Death rates from the four main sicknesses (cancer, respiratory diseases, infectious diseases and cardiovascular diseases) were falling throughout the 2000s including the crisis years - see Appendix Figure A2. Data on death rates were taken from the population census between 2006 and 2011. Death episodes were presented by cause of death, under the following code: 1-Cancer, 2-Respiratory Disease, 3-Infectious Disease, 4-Cardiovascular Disease, 5-Traffic Accidents, 6-Other Accidents, 7-Suicide, 8-Homicide.

the worst outcome, 1 is the default and 0 indicates a better than usual state of mind. To make interpretation easier we recoded the variables with 0 or 1, where 1 indicates a response worse than usual. The questions can be grouped in three categories. The first category are stress-related indicators and questions for general well-being (for example, *"In the last couple of weeks have you: lost much sleep over worry?; felt constantly under strain?; been feeling reasonably happy, all things considered?"*). The second category proves the decision-making capacity of individuals (for example, *"In the last couple of weeks have you: been able to concentrate on whatever you are doing?; felt capable of making decisions about things?"*). The third category contains questions about the individuals self-perception (for example, *"In the last couple of weeks have you: felt you were playing useful part in things?; being thinking of yourself as a worthless person?"*). While it could be argued that some of these answers simply capture general well-being it is harder to claim the same for other questions (for example, *"Have you been able to concentrate on whatever you are doing?"*). We compute an overall GHQ score, which is the unweighted average of the twelve answers for each respondent. In our sample, the average indicator is around 10 percent (and stable between 2006 and 2011). There is substantial variation in responses to the single GHQ components. For instance, about one fourth of the respondents answer "worse than usual" to the questions related to losing sleep over worry or to feeling constantly under strain, while only 3 percent report a higher propensity to think of themeselves as worthless individuals.

The second data set employed in our estimation is the Spanish Labor Force Survey (Encuesta de Población Activa - EPA). This survey is an ongoing research carried out every quarter and it targets households. Its main objective is to obtain data on the labor force and the various categories (employed and unemployed persons), as well as the population out of the labor market (inactive persons). The sample includes 65,000 interviewed households per quarter, which implies approximately 180,000 people. We use this data to capture the exposure of individuals to the economic shock.

Additionally, we use population data to build rates (death rate, unemployment rate). These data are gathered from the municipal registry (Padron Municipal) from 2000 to 2011. We use them disaggregated at the province level.

5 Health and Unemployment: Descriptive Evidence

We start our empirical analysis using information from the National Health Survey to investigate the correlation between unemployment status and several health indicators. We estimate the following OLS regression:

$$health_{ipt} = \alpha u_{ipt} + \boldsymbol{\beta}\mathbf{X}_{ipt} + \theta_p + \eta_t + \nu_{ipt} \quad (1)$$

where the dependent variable, $health_{ipt}$, is a measure of health for individual i, residing in region p at time t. The model includes a dummy variable to capture whether the respondent is unemployed, u_{ipt} (our main regressor of interest), a vector of individual socioeconomic characteristics, $\mathbf{X}_{ipt}$, fixed effects at the region, θ_p, and year level, η_t, and an error term ν_{ipt}.

Table 2 shows the first set of results. In the first column, the dependent variable is an indicator that takes value 1 if the respondent declares to be in *good* or *very good* health and 0 otherwise. This question is common to all the waves of the survey, and thus we include in estimation all the observations since 2001.[8] A gender dummy and an indicator for being younger than 40 are included as additional controls. All dependent variables are divided by their standard deviation to ensure comparability across survey questions.[9] The estimated coefficient on the unemployment dummy reported in column (1) implies that the unemployed have 20 percent of a standard deviation worse health than the employed (or that the unemployed are 8 percentage points more likely to have bad health). There is also strong evidence that men and young individuals report better health. These results still hold when controlling for education categories or finer age groups.

The remaining columns of Table 2 display the results of an alternative empirical specification employed in most of the paper. This new specification is based on a cell-level panel where cells are defined by three variables: age, sex and province of residence. The idea now is to compare changes in health outcomes within cells over time, holding a combination of individual characteristics (i.e. age and gender) and geography fixed. Accordingly, we include cell fixed effects θ_c in the specification in equation (1) and estimate the following model:

$$health_{ict} = \alpha u_{ict} + \theta_c + \eta_t + \nu_{ict}. \quad (2)$$

where the dependent variable, $health_{ict}$, is a measure of health for individual i, in cell c at time t, and the other variables are as in equation (1). The amount of data we have does not allow for a very fine-grained distinction in age groups across provinces. Thus in our main specification we

[8] The same results hold if we include earlier waves.

[9] This means all coefficients can be interpreted as the impact of unemployment on the dependent variable in terms of its standard deviation.

distinguish individuals that are older or younger than 40. Cells, c, are therefore defined by:

$$c : \{under40, province, male\}$$

which gives us $2 \times 51 \times 2 = 204$ cells. We think of these cells as a reasonable measure of the labor market an individual is in.[10] Note that when we use cell fixed effects we control for any unobservable difference that may exists between these different labor markets.

The new specification is quite demanding as it now exclusively exploits within-cell variation, allowing average health levels to vary across provinces for combinations of age and sex. Column (2) shows that our more stringent specification provides very similar results regarding general health. Columns (3) to (7) mantain the cell specification but restrict the sample to the comparable survey waves in 2006 and 2011 to look at additional outcomes. Column (3) shows that mental disorders are 16 percent of a standard deviation more likely among the unemployed (or that unemployed workers are 4 percentage points more likely to suffer from mental disorders). Other illnesses like chronic headaches and heart attacks are also more likely among the unemployed. However, here the magnitudes are much smaller. Heart attacks, for example, increase by only 6 percent of a standard deviation with unemployment.

The estimates in Table 2 highlight a clear correlation between mental health and, to a lesser extent, health in general and unemployment; however they are uninformative about which direction causality runs. Indeed, the OLS estimates of unemployment status on mental health combine two aspects. On the one hand, those who are in unemployment may have a different level of mental health than those who are employed. This will be the case if pre-existing mental health problems correlate with a higher likelihood of being fired and/or if mental disorders make job search harder.[11] On the other hand, entering (or remaining) unemployed may lead to isolation and economic stress, which can then trigger or amplify mental disorders. Only this latter effect is the causal impact of unemployment on health: the parameter we are after in our estimation. To this end, we employ an instrumental variable strategy based on the massive destruction of jobs in the construction resulting from the bursting of the Spanish housing bubble.

[10] In the robustness section we therefore construct different cells including the dimension of eduction.

[11] This latter pattern could be driven either by screening of employers or by a reduced capacity of effectively looking for jobs among the mentally ill.

6 Empirical Strategy

6.1 Theoretical Discussion

Our empirical analysis exploits the features of the recent Spanish economic crisis to identifying the causal effect of unemployment on health. We employ a two-stage least square estimation technique where the unemployment variable in equation (2) is instrumented using an individual's exposure to the collapse of employment opportunities in the construction sector. We argue that this instrument, in the context of the Spanish recession, satisfies the exclusion restriction, by generating job losses that are exogenous to unobserved individual characteristics. We further discuss that in our context re-entry into employment is almost impossible, a fact that bears important implications for the interpretation of our results. We next discuss these two assumptions theoretically in a static framework.[12]

To analyze the relevance of these two conditions let us first assume a situation where the effect of unemployment on health is homogeneous in the population. Accordingly we can estimate the following equation:

$$h_{it} = \alpha u_{it} + \mu_i + \epsilon_{it} \tag{3}$$

where h_{it} is (mental) health status of individual i at time t, u_{it} is a dummy equal one if the individual i is unemployed at time t, μ_i is an individual fixed effect and ϵ_{it} is an error term.[13] If being unemployed negatively affects an individual's health, we should expect the coefficient on the unemployment indicator to be negative ($\alpha < 0$).

As discussed above, there are many reasons to expect the individual unemployment status to be correlated with the individual fixed effect: $cov(u_{it}, \mu_i) \neq 0$. In particular, under the realistic assumption that healthier individuals are less likely to be unemployed (e.g. if productivity is increasing in health, employers prefer hiring healthier individuals), we would have $cov(u_{it}, \mu_i) < 0$. The OLS estimator in equation (3) can be written as:

$$\begin{aligned} \alpha_{OLS} &= E(h_{it}|u_{it} = 1) - E(h_{it}|u_{it} = 0) \\ &= \alpha + E(\mu_i|u_{it} = 1) - E(\mu_i|u_{it} = 0). \end{aligned} \tag{4}$$

If individuals who are unemployed have on average lower health than those employed, we would

[12] A derivation in a dynamic framework is available from the authors by request.

[13] For simplicity we remove the geographic dimension in this part of the discussion.

have that $E(\mu_i|u_{it}=1)-E(\mu_i|u_{it}=0)<0$. In this case, the OLS estimator would be downward bias. Given that we expect the parameter of interest α to be negative, the OLS estimate would be larger in magnitude than the underlying causal parameter exagerating the negative effect that being unemployed may produce on health. The OLS estimate, therefore, would be larger in absolute value than an IV estimator that managed to retrieve the actual parameter $\alpha : |\alpha_{OLS}| > |\alpha|$.

However, there is no reason to expect the effect of job loss to be homogenous in the population. On the contrary, we can expect different people to react differently to the experience of being unemployed. Being laid off can be a psychologically devastating experience for some whereas for others it may just represent an unfortunate accident in life. Clearly, several factors determine the impact of unemployed on each individual. For example, workers who can rely on savings, family wealth or spouse's income will not have to immediately worry about the economic consequences that losing a job may have. Beyond short-term concerns generated by the income loss, the magnitude of the mental impact of unemployment will also depend on individual psychological traits such as self-esteem and self-confidence, on whether the individual experienced unemployment before, on the social stigma that the individual attaches to the unemployment status, etc. Further, expectations should play a crucial role. The fact of being laid off may generate more stress if the event was unexpected and stress may increase if the individual deems it difficult to find a new job in the near future.

Under the assumption that the effect of unemployment is heterogeneous in the population, equation (3) can be re-written as:

$$h_{it} = \alpha_i u_{it} + \mu_i + \epsilon_{it} \tag{5}$$

where now the coefficient α_i varies at the individual level. Using the notation in the policy evaluation literature, we have:

$$\begin{aligned} h_{it} &= \alpha^{ATE} u_{it} + (\alpha_i - \alpha^{ATE}) u_{it} + \mu_i + \epsilon_{it} \qquad (6) \\ &= \alpha^{ATE} u_{it} + e_{it} \end{aligned}$$

where ATE refers to the *average treatment effect* of unemployment in the population. That is, $\alpha^{ATE} = E(\alpha_i)$ and $e_{it} = (\alpha_i - \alpha^{ATE})u_{it} + \mu_i + \epsilon_{it}$.

Following with this notation, the expected health among the unemployed can be expressed as:

$$E[h_{it}|u_i = 1] = \alpha^{ATE} + E[\mu_i|u_i = 1] + E[(\alpha_i - \alpha^{ATE})|u_i = 1], \tag{7}$$

and among the employed:

$$E[h_{it}|u_i = 0] = E[\mu_i|u_i = 0]. \tag{8}$$

The OLS estimator is:

$$\begin{aligned} \alpha_{OLS} &= E[h_{it}|u_i = 1] - E[h_{it}|u_i = 0] \\ &= \alpha^{ATE} + E[\mu_i|u_i = 1] - E[\mu_i|u_i = 0] + E[(\alpha_i - \alpha^{ATE})|u_i = 1]. \end{aligned} \tag{9}$$

The selection bias in the presence of heterogeneity has two components. First, the term $[E[\mu_i|u_i = 1] - E[\mu_i|u_i = 0]]$ which also appears in the case of homogeneous effects and is negative if healthier individuals are less likely to be unemployed. Second, the term $E[(\alpha_i - \alpha^{ATE})|u_i = 1]$ which reflects the possibility of differences across individuals in the effect of unemployment. In this context, we can expect individuals who suffer the most from unemployment to be less likely to be jobless. Indeed, these individuals have strong incentives to exert maximum effort and to lower their reservation wage to find a new job. Therefore, individuals with higher potential (mental) health loss from unemployment will have a lower probability of entering unemployment if employed and a higher probability of finding a job if unemployed. This implies that if unemployed workers are those who suffer the less from being jobless, they should have an α_i above the average (which we expect to be negative) in the population. Hence, we expect the last term in equation (9) to be positive: $E[(\alpha_i - \alpha^{ATE})|u_i = 1] > 0$.[14]

Therefore, in the presence of heterogeneity we have two sources of bias in the OLS estimator and they have opposite signs. Differently from the homogenous case, it is now unclear whether the OLS estimator would over- rather than under-estimating the causal parameter of interest. The bias will depend on whether selection in and out of unemployment correlates with health status, with the health loss in unemployment or with both.

In order to retrieve the causal effect of unemployment one would need an instrument that is uncorrelated with both the unobservable health status of workers, μ_i, and with the unobservable individual "health effect" from being unemployed, α_i. In other words, one would need an exogenous shock that pushes individuals into unemployment irrespective of their unobservables characteristics. The literature has proposed to use plant closures as instrument in this context (Sullivan and von Wachter 2009, Eliason and Storrie 2009a, Browning and Heinesen 2012 and Black et al. 2015). When a plant shuts down all employees are generally laid off and, for these

[14] Recall that we expect α^{ATE} to be negative

workers, the entry into unemployment is orthogonal to their unobservable individual characteristics. The instrument we propose in this paper is based on the collapse of an entire sector - the construction sector in Spain - and follows a logic similar to the plant closure approach. Workers employed in this sector suddenly lost their jobs, irrespectively of their underlying health status and of the effect that being unemployed may produce on their health (i.e. orthogonally to their unobservable μ_i and α_i in the equation (3)).

Both the plant closure and the sector closure arguably generate an initial quasi-random assignment to unemployment. However, from the day after being laid off affected workers will start reacting differently to their new job status. In particular, we should expect those who fear to suffer the most from being jobless to actively search for employment. Over time, this endogenous selection out of unemployment will imply that those who remain unemployed suffer less from being jobless. We can interpret this selection as (endogenous) imperfect compliance with respect to the initial random assignment. In this regard, the plant and the sector closure differ along one important dimension. Workers laid off due to a negative idiosyncratic shock that hit their plant will look for a job in a labor market that is generally not experiencing adverse conditions. They may relatively quickly move out from unemployment, find a job in a new firm that values their skills and minimize the damage that remaining unemployed may cause on their physical and mental health. In contrast, workers who become unemployed because of the collapse of their entire sector of employment may have a very hard time in finding an alternative occupation. They will likely be trapped in unemployment until they manage to update their skills and change sector. As documented in section 3, the collapse of the construction sector led to both a large increase in unemployment and to a dramatic increase in its duration, with exit rates from unemployment being driven close to zero.

These differential unemployment exit rates also imply that becoming jobless due to the collapse of a sector is a much more "severe treatment" than losing the job due to a plant closure. Not only the treatment is more persistent but agents who anticipate this longer persistence may suffer even more from being in that condition. If being fired is always a disappointing experience, entering unemployment with the expectation of remaining in that status for a long period may potentially magnify the distress of lossing a job. Using our identification strategy, therefore, we would expect to observe larger effects on health with respect to papers that instead based their identification on firm closures.

6.2 Construction of the Instrument

The previous discussion highlights that we need a variable that captures exogenous job losses and homogenous re-employment probabilities across workers. The evolution of employment in the Spanish construction sector can serve as an instrument for both. First, the collapse of the sector meant that individual fortunes were driven by an exogenous shock. Between 2007 and 2012, employment fell by more than 60 percent.[15] Many businesses had to close: bankruptcies in construction shot up from just around 200 per year in the period 2005 to 2007 to around 1500 per year in the period 2008 to 2010, and they reached 1900 in 2011. The increase in bankruptcies was not only in absolute terms but also in relative terms: about 33 percent of all bankruptcies in Spain between 2008 and 2010 were by companies in construction.[16] This suggests that if we use employment in construction as an instrument for unemployment we will be capturing job losses due mostly to plant closures from the year 2007 onwards. Workers in construction were often unskilled with a training very specific to the sector. Thus as a result of the collapse they had a hard time in finding a new job and were trapped in unemployment for a long period.[17]

To form the instrument we employ the exposure of different groups to the construction sector. The idea behind our identification strategy is to use changes in the demand for labor at the aggregate level as an instrument for unemployment at the cell level. Our instrument builds on the strategy in Bartik (1991) and Blanchard and Katz (1992) where the industrial composition of the economy at an initial period is used to predict exogenous changes in employment over time.

To implement our instrument we use the EPA data and aggregate to the cell level to generate to generate a measure of the employment shock in the different sectors of the Spanish economy. As before, we use cells spanned by three characteristics - age, sex and province of residence:

$$c = \{under40, province, male\}.$$

For these cells we construct employment shares by 9 industries, j, in 2000. We refer to these shares as $s_{c,j,2000}$. As a second step we calculate the change in aggregate employment in industry j in year t at the national level as:

$$g_{jt} = \left(E_{j,t} - E_{j,t-1}\right)/E_{j,t-1}.$$

[15] See Appendix figure A1. Source is the EPA data.

[16] Source: Spanish Statistical Office.

[17] See Figure 5b for the evolution of unemployment duration in the construction sector over the period.

We focus on employment changes as it gives us a measure of the intensity of employment shocks in each period. Both our first and second stage results are robust to using employment levels or the change in levels.

Figure 6 shows employment growth in Spain. We plot the average employment growth for all sectors with a dashed line and employment growth in construction with a solid one. The picture shows that until 2007 employment was growing in Spain, but the boom was particularly large in construction where growth was above average in all years. However, in 2007 the shock hit and employment fell across the board. The shock was particularly strong in construction where employment shrank by more than 20 percent in 2009 and growth was below -10 percent in all years after 2007. As a result, more than 60 percent of all jobs that existed in construction in 2007 were lost in the following years. This was a very drastic development even when compared to the generally dramatic change in the Spanish labor market, where most sectors shed about 15 percent of employment after 2007.

We use the interaction between the share of employment in construction at the cell level in 2000 (i.e. $s_{c,constr,2000}$) and the annual employment growth in construction at the national level (i.e. $g_{constr,t}$) as our main instrument for cell unemployment. That is:

$$constrcIV_{c,t} = s_{c,constr,2000} * g_{constr,t}.$$

As an alternative we also employ an instrument based on total employment growth:

$$employmentIV_{c,t} = \sum_j s_{c,j,2000} * g_{j,t}.$$

The idea behind this instrumental variable approach is that aggregate changes in employment are not driven by cell specific characteristics. Moreover, its interaction with the industry composition in 2000 ensures that the exposure of cells to construction is pre-determined.

Our first stage regression then follows:

$$u_{it} = \delta construcIV_{c,t} + \theta_c + \eta_t + \nu_{it} \tag{10}$$

where the unemployment status of individual i, in cell c, at time t, is regressed on the cell-specific instrument. The regression includes a full set of cell fixed effects, θ_c, and year fixed effects, η_t. In this specification the parameter δ captures the change in unemployment for individuals which can be explained by the change in job opportunities in construction.

7 Results

7.1 First-Stage Estimates

Table 3 reports variations of the first stage regression in equation (10). Column (1) to (6) report results for all the waves in the National Health Survey 2001, 2003, 2006 and 2011. Column (1) employs all industries in forming the instrument. There is a clear negative correlation between employment growth and the level of unemployment at the cell level. In column (2) the predicted level of total employment growth is divided into the construction and all other industries. The results show that employment in construction is a much better predictor of unemployment. This is consistent with the much more rapid decline in the employment of this sector observed in Figure 6. The estimates in column (3) only include employment growth in construction and suggest that the shrinking of the 15 percent of employment prior to 2011 led to an unemployment rate of more than 30 percent in cells that had all their employment in the construction sector in 2000. This finding is robust to various modifications with respect to the definition of cells (columns (4) and (5)) and also does not change if we focus on just the last two waves in 2006 and 2011 (column (6)). However, in column (7) we show that the instrument is relatively weak if we just study the first three waves 2001, 2003 and 2006.

In our main analysis we employ as a first-stage the results in column (6). It provides fitted values of the unemployment rate of up to 58 percent. The average change across the two waves is an increase of 12 percentage points and the maximum increase is 24 percentage points.[18] The group with the biggest increase are men below 40 in provinces with large construction sectors.

7.2 Main Results

Table 4 presents the main results. The estimates are obtained from the second-stage regression:

$$health_{ict} = \alpha \hat{u}_{ct} + \theta_c + \eta_t + \nu_{ict} \tag{11}$$

where $\hat{u}_{ct}$ is the predicted unemployment from equation (10). In this regression we need to cluster at the cell level since all variation in $\hat{u}_{ct}$ comes from this level.[19] As before we control for cell and year fixed effects.

[18] In appendix Figure A3 we report kernel densities of the fitted values in column (6).

[19] This is despite the fact that we instrument for unemployment at the individual level. We return to this point below.

The results in Table 4 are obtained from the comparison of health in the two latest waves, 2006 and 2011. We divide all the dependent variables according to their standard deviation. We find a strong and negative effect on reports of general good health (-0.74 standard deviations) and large effects on mental disorders with and without diagnosis by a doctor (about 1.1 standard deviations). Thus the estimates indicate that a 10 percentage points increase in unemployment driven by the exogenous shock, increases mental disorders by about 3 percentage points (or that mental disorders are 30 percentage points more likely among unemployed workers).

The remaining columns in Table 4 confirm the findings on mental health using the GHQ questionnaire on mental disorders. Remember that all questions here are coded such that positive coefficients indicate a "worse than usual" answer. Column (4) reports that unemployment leads to an increase of 0.9 standard deviations in the mean score across all categories in the questionnaire. On each question we find a positive and fairly large coefficient. However, only a few are significantly different from zero. In particular, the unemployed are 1.3 standard deviations more likely to report that they feel constantly under strain and 0.9 standard deviations more likely to report that they do not feel a useful part of society. There is also some evidence that the unemployed are more likely to feel that they cannot overcome their difficulties and are unable to concentrate.

Note that the IV estimates of the effect of unemployment on mental health are larger in magnitude than the OLS reported in Table 3. This larger effect corresponds to the sub-sample of the population from where the effect is identified, namely construction workers. As discussed, employment in construction fell by about 60 percent between 2007 and 2013 and the large majority of those who lost their job in construction, 2.7 percent of the active population, slipped into unemployment spells that lasted longer than one year. Accordingly, while workers negatively affected by an idiosyncratic shock can quickly find a new job in any other firm, workers laid off by the shut down of an entire sector find themselves trapped into unemployment. Failure to re-enter employment for those who try hardest might have very high costs on mental health. This view is corroborated by the finding that affected individuals felt under strain and useless.[20] It is important to note that these effects are driven by changes at the cell level, i.e. by changes within each of the over fifty Spanish provinces.[21] That means they cannot be explained by changes in the local economic climate or public sector spending.

[20] We also confirmed that, in the OLS, longer duration correlates with worse reported mental health.

[21] We show in the robustness section that our findings strengthen when we control for province/year fixed effects.

In light of our theoretical discussion the coefficient we identify with our instrument is a *Local Average Treatment Effect* (LATE). This effect is defined on a specific population of *compliers*: those workers who entered unemployment as a consequence of the collapse of the construction sector. Note that the population of unemployed workers after the crisis hit Spain can be distinguished in two groups. A first group of unemployed workers called *always-takers:* they would have been unemployed even in the absence of the crisis. We can think of this sub-population as the workers who would have been unemployed even in normal times and we can expect them to be those who suffer relatively less from unemployment (i.e. those who have relatively low α_i). The second group of unemployed workers are those who were pushed into unemployment by the crisis, the *compliers*: these are individuals who would have been employed had the crisis not hit. We can therefore expect these individuals to have average α_i well above those of the *always-takers.* Given the characteristics of our IV strategy, we identify the average treatment effect precisely among this latest group of the population.

There is an alternative and complementary explanation to the large size of our IV results. In our previous discussion, we assume that the identifying condition of the instrument holds at the individual level. However, the variation in the instrument is only at the cell level. It could well be that the effects of high unemployment in a cell spilled over to the employed. This is reasonable as cells (i.e. male, under 40, province of residence) are precise enough to capture local labor markets. The treatment of unemployment is then literally at the cell not at the individual level. This interpretation would not violate the restriction assumption on the IV if the spill-over works through past experience of unemployment and the fear of (long term) unemployment amongst those who have work.[22]

7.3 Additional Results

Tables 5 and 6 report additional results. In Table 5 we report IV estimates of the effects of unemployment on other health outcomes. We find some weak evidence that chronic headaches become more likely as a result of becoming unemployed; but otherwise we find very few consistent results. This is interesting as it suggests that unemployment caused by the shock did not, yet, lead to a general deterioration of health. For example, the fact that the OLS results in Table

[22] This interpretation is also consistent with the findings in Sullivan and von Wachter (2009); the employment shock of a plant closure affects individuals who find work later.

2 regarding stroke go away suggests that these were probably driven by reverse causality. In column (5) of Table 5 we show that the unemployed are more likely to use medicine. This is in line with the finding that general health and in particular mental health deteriorates.

Finally, we analyze the effect of unemployment on suicides. Figure 7 reports the level of suicides per 100,000 population which we calculate from deaths and population numbers. Suicide rates were falling from 7.6 in 2000 to 6.6 (per 100,000) in 2011. However, the fall is not uniform but interrupted by two large waves. The second wave starts exactly in 2007. In Table 6 we confirm that the increase in suicides during this second period took place in those cells that were hardest hit by unemployment. To do this we take unemployment rates at the cell level and run a IV regression of ln(suicides) on unemployment which follows equation (11). The only difference with respect to our main results is that we use unemployment rates from the EPA and therefore have yearly data for the period 2001-2011. Column (1) indicates that, overall, there is no consistent relationship between unemployment and suicides in the period 2001-2011. The positive association between unemployment and suicides only becomes apparent if we focus on the years after 2006. The relationship is then robust to the inclusion of ln(population) on the right hand side of equation (11), province time trends and modifications in the definition of cells. This result would suggest that an increase of the unemployment rate by 10 percentage points leads to an increase in suicides by about 45 percent. This is an increase of about 3 deaths in 100,000 population per year. However, this interpretation is problematic given the earlier peak which fell into a period of falling unemployment.

7.4 Robustness

We now present a number of robustness checks to our main results in Tables 7, 8 and 9. First, we use a different division in cells as introduced in Table 3. Our first alternative uses a finer distinction by age. That is:

$$c = \{under30, over50, province, male\}$$

and run the same regressions as in Table 4. Note that we now have 306 cells and control for many more cell fixed effects. Results are unaffected by this (Table 7). If anything the results from the GHQ survey strengthen. We then add college education as an additional dimension:

$$c = \{under40, province, male, college\}$$

and, again, control for cell fixed effects at this level (408 cells). Under this alternative definition the results are also not significantly affected (Table 8). The coefficient on the general health indicator drops and becomes insignificant while several variables in the GHQ are now estimated with more precision.

Table 9 presents a number of additional robustness checks. Column (1) uses employment growth in the previous three years to instrument for unemployment. Results remain unchanged. This is also true if we just use employment levels or employment changes. We also tried using all employment and again our results are robust. Column (2) uses only variation at the province level, clustering also only at this level. We still find a positive coefficient but the standard errors are now much larger, and the coefficient becomes insignificant. This suggests that within-province variation is the main driver of our results. Column (3) uses the unemployment rate at the cell level constructed from the Spanish Labor Force Survey instead of individual employment. Our results are robust to this different way of looking at the data. In column (4) we add the inactive population (pensioners, students, individuals working from home) and our results on unemployment do not change.

The, perhaps, most important robustness checks of our results are in columns (5) to (7). Here we add province/time fixed effects to our main specification. This means we identify the effect of unemployment entirely from within-province variation so that changes in local availability of credit or public sector spending which are only changing at the province level are controlled for. Our results are robust to this and even strengthen slightly. This is also true for all other measures of mental health presented in Table 4. In column (6) we add the waves 2001 and 2003. Unfortunately, the questions regarding mental disorder were not the same between 2001/2003 and 2006/2011 so that we need to switch to the more generic question of overall good health. The coefficient is very similar to the one in our main table (Table 4, column (1)). In column (7) we include a time trend for men. This is based on the idea that our construction sector instrument could be capturing the relative movement of mental health between men and women. Our results strengthen under this alternative specification, suggesting that the construction sector instrument does not merely capture long term gender trends. Our findings can only be explained by the fact that self-reported health first improved in cells which were close to the construction sector and then deteriorated. The relative peak in health was reached in 2006 - at a time when unemployment in these cells was lowest.

8 Conclusion

In this article we analyze the relationship between unemployment and mental health in the context of the severe economic crisis in Spain. We exploit the extreme circumstances in the labor market of construction workers to identify the causal effect of unemployment on health. We argue that job destruction as a result of the burst of the housing bubble represented an exogenous shock to labor demand that affected both the probability of being laid off as well as that of re-employment. Accordingly, our instrumental variable approach is able to estimate the causal effect of unemployment on health net of workers' selection in and out of unemployment. The IV estimates suggest that mental disorders in this group are almost 30 percentage points more likely than in the employed population. The large magnitude of this effect responds to the fact that identification comes from a group of workers that were unable to escape unemployment after the collapse of the construction sector.

Our findings raise the concern that a significant share of the Spanish labor force could get trapped in a cycle of skill mismatch and mental disorder. Long-term unemployment stood at 12 percent of the active population in 2012. The finding that this group is not only suffering from an income loss but from a loss of (mental) health is worrying on its own right. In addition, the combination of skill mismatch and the inability to search and embrace new labor market opportunities in such a large part of the population is a liability for the Spanish economy as a whole.

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Table 1: Summary Statistics

Variable	Mean	Std. Dev
Panel A - NHS (2001, 2003, 2006, 2011)		
Individual characteritics		
age	39,262	11,137
male	0,583	0,493
secondary education	0,559	0,496
college education	0,220	0,414
unemployed	0,162	0,369
General Health		
reported good health	0,789	0,408
Observations	46247	
Panel B - NHS health questions (2006, 2011)		
Individual characteritics		
age	39,696	11,017
male	0,569	0,495
secondary education	0,590	0,492
college education	0,224	0,417
unemployed	0,186	0,389
present or previous employment in construction	0,109	0,311
Health and Mental Health		
reported good health	0,790	0,407
chronic backpain diagnosed	0,224	0,417
chronic headache diagnosed	0,093	0,290
heart attack diagnosed	0,029	0,167
stroke diagnosed	0,004	0,063
mental disorder diagnosed by doctor	0,084	0,278
mental disorder reported	0,087	0,283
GHQ Mental Health Survery		
mental disorder GHQ questionaire average score	0,108	0,192
1) lost sleep	0,240	0,427
2) felt under strain	0,257	0,437
3) unable to enjoy activities	0,102	0,303
4) unhappy or depressed	0,141	0,348
5) feeling unhappy	0,059	0,236
6) unable to concentrate	0,114	0,318
7) unable to make decisions	0,042	0,201
8) unable to overcome difficulties	0,120	0,325
9) unable to face problems	0,056	0,229
10) feeling useless	0,064	0,245
11) lost self confidence	0,065	0,246
12) worthless person	0,032	0,177
Observations	24856	

Table 2: Unemployment and Health (OLS)

VARIABLES	(1) reported good health	(2) reported good health	(3) mental disorder diagnosed by doctor	(4) chronic backpain diagnosed by doctor	(5) chronic headache diagnosed by doctor	(6) heart disease diagnosed by doctor	(7) stroke diagnosed by doctor
unemployed	-0.205***	-0.203***	0.163***	0.0265	0.0426*	0.0557**	0.0454**
	(0.0204)	(0.0204)	(0.0232)	(0.0213)	(0.0218)	(0.0227)	(0.0229)
male	0.0613***						
	(0.00557)						
under 40	0.123***						
	(0.00554)						
province and year fixed effects	yes	no	no	no	no	no	no
cell and year fixed effects	no	yes	yes	yes	yes	yes	yes
survey years	2001-11	2001-11	2006-11	2006-11	2006-11	2006-11	2006-11
Observations	46,330	46,330	25,544	25,544	25,544	25,544	25,544
R-squared	0.041	0.047	0.049	0.047	0.061	0.050	0.019

Robust standard errors clustered at the province level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. Cells are formed by all possible interactions between a dummy for male, a dummy for under 40 and 51 province dummies (2x2x51 = 204 cells).

Table 3: Construction Sector Employment as Predictor of Unemployment

VARIABLES	(1) unemployed	(2) unemployed	(3) unemployed	(4) unemployed	(5) unemployed	(6) unemployed	(7) unemployed
employment growth	-2.571***						
	(0.603)						
employment growth (construction)		-2.340***	-2.258***	-2.325***	-2.429***	-2.454***	-16.48
		(0.582)	(0.451)	(0.395)	(0.420)	(0.456)	(11.08)
employment growth (not construction)		-0.278					
		(0.968)					
cell fixed effects	yes	yes	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes	yes	yes
survey years	2001-11	2001-11	2001-11	2001-11	2001-11	2006-11	2001-2006
Observations	46,358	46,358	46,358	46,275	46,358	25,544	35,579
R-squared	0.067	0.067	0.067	0.085	0.081	0.068	0.044

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample are the years 2001 to 2011 except for column (6) where the sample is only 2006 and 2011 and column (7) where the sample is 2001 to 2006. Regressions in columns (1), (2), (3) , (6) and (7) use cells defined by provinces, sex and a dummy of age<40. Column (4) uses two age dummies <30, >50. Column (5) instead adds a dummy for college education.

Table 4: Main Results - Mental Health and Unemployment (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						In the last couple of weeks have you…		
VARIABLES	reported good heatlh	mental disorder diagnosed by doctor	mental disorder reported	summary score GHQ12 mental health survery	Lost much sleep over worry?	Felt constantly under strain?	Been able to enjoy your normal day-to-day activities?	Been feeling unhappy and depressed?
unempl	-0.741**	1.103**	1.169**	0.911*	0.447	1.337***	0.370	0.686
	(0.364)	(0.498)	(0.498)	(0.470)	(0.348)	(0.496)	(0.368)	(0.454)
Observations	25,544	25,544	25,544	24,914	25,082	25,055	25,061	25,060
R-squared	0.010			0.030	0.041		0.028	0.027

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
				In the last couple of weeks have you…				
VARIABLES	Been feeling reasonably happy, all things considered?	Been able to concentrate on whatever you are doing?	Felt capable of making decisions about things?	Felt that you couldn't overcome your difficulties?	Been able to face up to your problems?	Felt that you were playing a useful part in things?	Been losing self-confidence in yourself?	Been thinking of yourself as a worthless person?
unempl	0.572	0.859*	0.334	0.772*	0.238	0.886**	0.255	0.150
	(0.477)	(0.446)	(0.409)	(0.399)	(0.482)	(0.370)	(0.504)	(0.535)
Observations	25,059	25,102	25,075	25,063	25,046	25,035	25,045	25,025
R-squared	0.027		0.026	0.020	0.024	0.020	0.034	0.031

Robust standard errors clustered at the cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. In columns (4) to (16) higher values are always more negative outcomes. Variables are recoded such that they take values 0 (better and as usual) and 1 (worse than usual). The summary scores is the average score divided by 12. All regressions control for cell and year fixed effects. Cells are defined by provinces, sex and a dummy of age<40.

Table 5: Other Health Outcomes

VARIABLES	(1) chronic backpain diagnosed by doctor	(2) chronic headache diagnosed by doctor	(3) heart disease diagnosed by doctor	(4) stroke diagnosed by doctor	(5) takes medicines
unemployed	0.659	0.873*	0.519	-0.157	1.005**
	(0.551)	(0.505)	(0.319)	(0.301)	(0.469)
cell fixed effects	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes
Observations	25,544	25,544	25,544	25,544	25,544
R-squared	0.005			0.004	

Robust standard errors clustered at the cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. Cells are defined by provinces, sex and a dummy of age<40.

Table 6: Unemployment and Suicides (IV)

	(1)	(2)	(3)	(4)	(5)
VARIABLES			ln(suicides)		
unemployment rate	-0.303	4.231**	4.706**	4.979**	3.846**
	(0.808)	(1.981)	(2.008)	(2.122)	(1.624)
cell fixed effects	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes
control of ln(population)	no	no	yes	yes	yes
province time trend	no	no	no	yes	no
survey years	2001-11	2007-11	2007-11	2007-11	2007-11
Observations	2,035	921	921	921	1,283
R-squared	0.944	0.950	0.952	0.958	0.939

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Unmployment rate is the unemployment rate at the cell level. Column (1) uses data from 2001 till 2011. All other columns use data from 2007 to 2011. Columns (1) to (4) use cells defined by provinces, sex and a dummy of age<40. Column (5) uses two age dummies <30, >50.

Table 7: Mental Health and Unemployment (IV), 3 age categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						In the last couple of weeks have you…		
VARIABLES	reported good heatlh	mental disorder diagnosed by doctor	mental disorder reported	summary score GHQ12 mental health survery	Lost much sleep over worry?	Felt constantly under strain?	Been able to enjoy your normal day-to-day activities?	Been feeling unhappy and depressed?
unempl	-0.646*	1.044**	1.083***	0.828*	0.371	1.192**	0.324	0.811*
	(0.337)	(0.426)	(0.398)	(0.446)	(0.350)	(0.482)	(0.375)	(0.436)
Observations	25,544	25,544	25,544	24,914	25,082	25,055	25,061	25,060
R-squared	0.010			0.030	0.041		0.028	0.027

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
				In the last couple of weeks have you…				
VARIABLES	Been feeling reasonably happy, all things considered?	Been able to concentrate on whatever you are doing?	Felt capable of making decisions about things?	Felt that you couldn't overcome your difficulties?	Been able to face up to your problems?	Felt that you were playing a useful part in things?	Been losing self-confidence in yourself?	Been thinking of yourself as a worthless person?
unempl	0.519	0.782*	0.279	0.660	0.232	0.861**	0.143	0.104
	(0.412)	(0.418)	(0.379)	(0.407)	(0.438)	(0.367)	(0.434)	(0.478)
Observations	25,059	25,102	25,075	25,063	25,046	25,035	25,045	25,025
R-squared	0.027		0.026	0.020	0.024	0.020	0.034	0.031

Robust standard errors clustered at the cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. In columns (4) to (16) higher values are always more negative outcomes. Variables are recoded such that they take values 0 (better and as usual) and 1 (worse than usual). The summary scores is the average score divided by 12. All regressions control for cell and year fixed effects. Cells are defined by provinces, sex a dummy for age<30 and a dummy for age>50.

Table 8: Mental Health and Unemployment (IV), dummy for college

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						In the last couple of weeks have you…		
VARIABLES	reported good heatlh	mental disorder diagnosed by doctor	mental disorder reported	summary score GHQ12 mental health survery	Lost much sleep over worry?	Felt constantly under strain?	Been able to enjoy your normal day-to-day activities?	Been feeling unhappy and depressed?
unempl	-0.432	0.923**	0.974**	0.855**	0.396	1.248***	0.401	0.658*
	(0.345)	(0.391)	(0.394)	(0.389)	(0.325)	(0.411)	(0.297)	(0.381)
Observations	25,461	25,461	25,461	24,856	25,021	24,994	25,000	25,000
R-squared	0.061			0.047	0.053		0.036	0.041

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
				In the last couple of weeks have you…				
VARIABLES	Been feeling reasonably happy, all things considered?	Been able to concentrate on whatever you are doing?	Felt capable of making decisions about things?	Felt that you couldn't overcome your difficulties?	Been able to face up to your problems?	Felt that you were playing a useful part in things?	Been losing self-confidence in yourself?	Been thinking of yourself as a worthless person?
unempl	0.480	0.710*	0.365	0.680**	0.333	0.777**	0.143	0.178
	(0.391)	(0.381)	(0.387)	(0.343)	(0.387)	(0.317)	(0.394)	(0.446)
Observations	24,999	25,041	25,014	25,002	24,987	24,974	24,985	24,966
R-squared	0.041	0.000	0.035	0.040	0.033	0.042	0.041	0.040

Robust standard errors clustered at the cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. In columns (4) to (16) higher values are always more negative outcomes. Variables are recoded such that they take values 0 (better and as usual) and 1 (worse than usual). The summary scores is the average score divided by 12. All regressions control for cell and year fixed effects. Cells are defined by provinces, sex a dummy for age<40 and a dummy for college education.

Table 9: Robustness

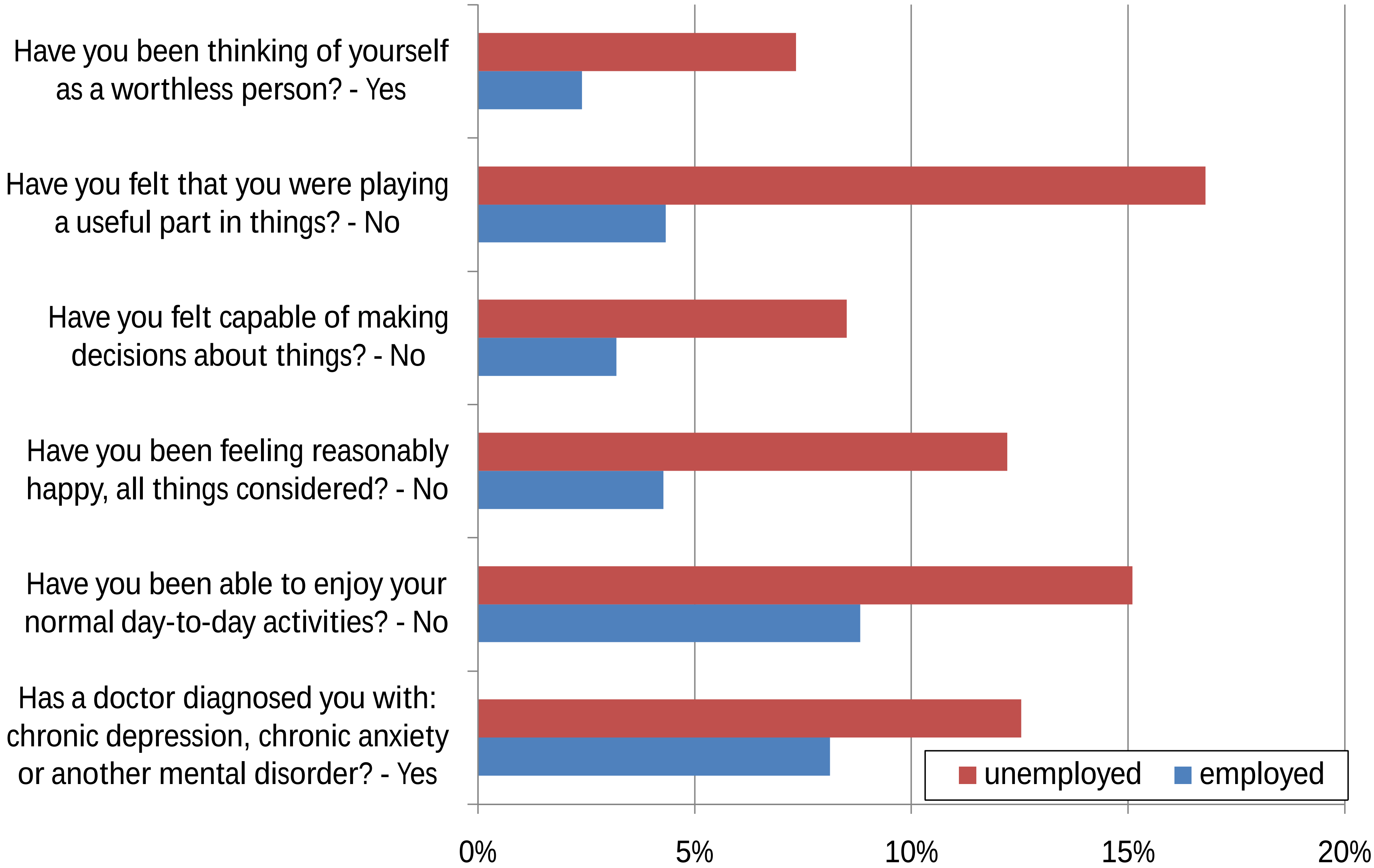
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	growth in last three years as IV	construction employment at province level as IV	average unemployment at cell level	including inactive population	province/time fixed effects	including early waves	including early waves and male time trend
VARIABLES	mental disorder diagnosed by doctor					reported good heatlh	
unemployed	1.103**	0.415	1.880**	1.139**	1.313***	-0.847**	-1.632***
	(0.498)	(1.468)	(0.780)	(0.571)	(0.476)	(0.379)	(0.433)
cell fixed effects	yes	no	yes	yes	yes	yes	yes
year fixed effects	yes	no	yes	yes	no	no	no
province/year fixed effects	no	no	no	no	yes	yes	yes
Observations	25,544	25,544	25,544	36,563	25,544	46,330	46,330
R-squared		0.028	0.044			0.003	

Robust standard errors clustered at the cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All dependent variables are weighted by their standard deviation. Cells are defined by provinces, sex and a dummy for age<40. Columns (1) to (5) include data for years 2006 and 2011. Columns (6) and (7) include years 2001, 2003, 2006 and 2011. Column (3) uses unemployment at the cell level from the EPA instead of the dummy for unemployment from the NHS. Column (3) controls for sex, dummy for age under 40, province and year fixed effects. Column (5) controls for province/time fixed effects.

Table A1: Diagnosed Mental Disorders in 2006 and 2011

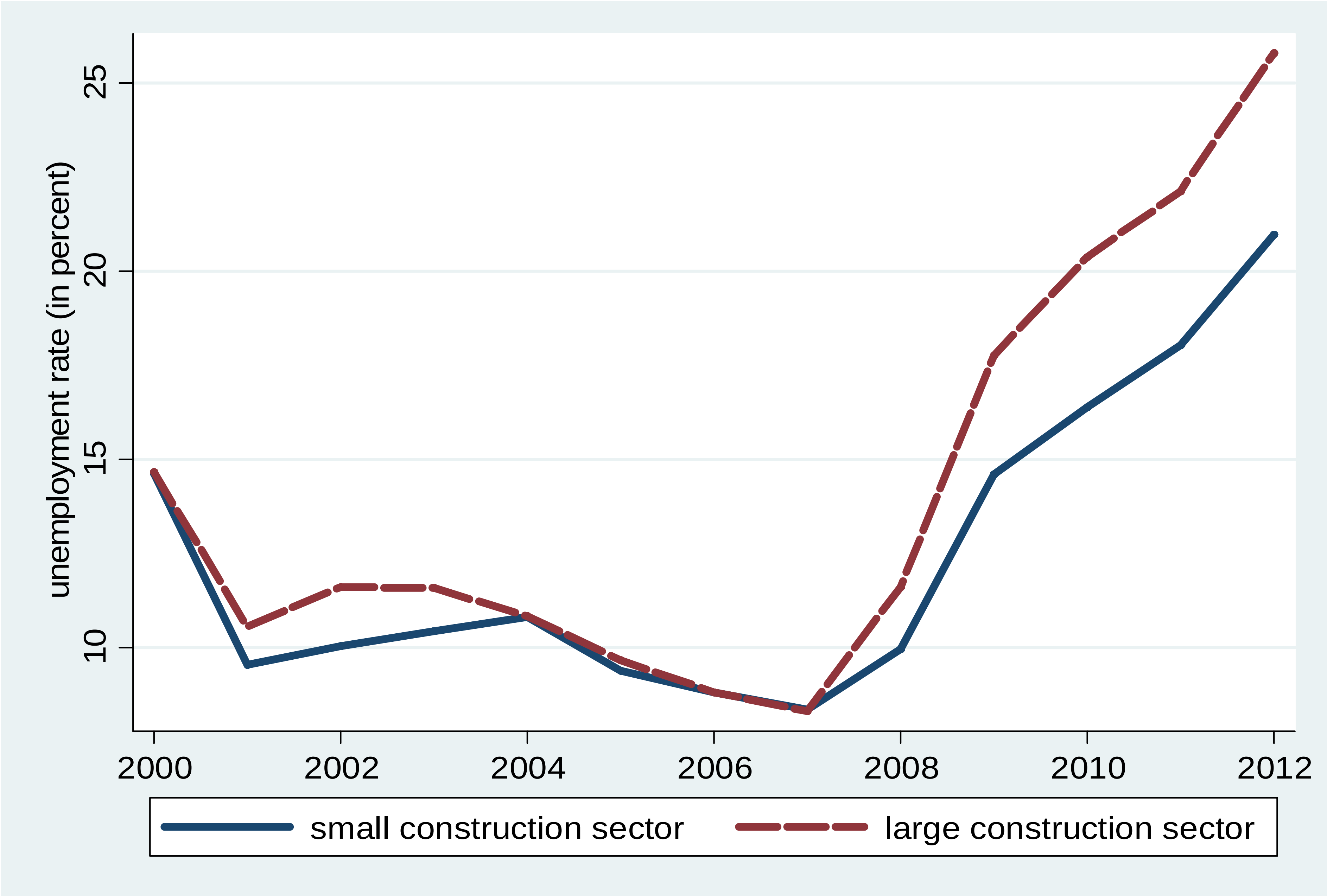
mental disorder diagnosed by doctor	2006	2011	difference
all individuals	0,098	0,072	-0,025
present or previous employment in construction	0,052	0,053	0,001
present or previous employment not construction	0,104	0,075	-0,029

Figure 1: Unemployment and Mental Health



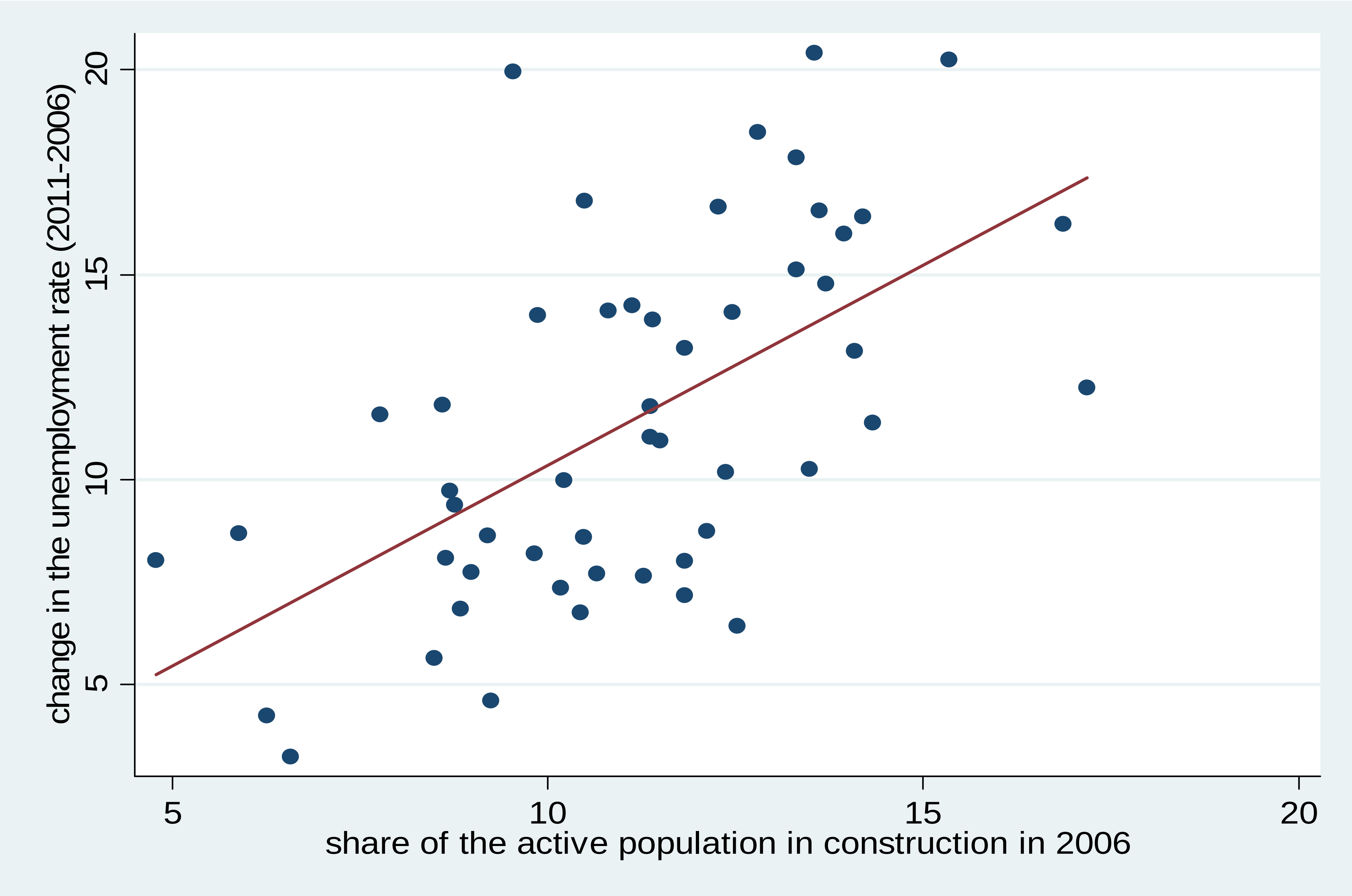
Note: Yes and No respectively represent “worse than usual” answers.
Source: Spanish National Health Survey. Years 2006 and 2011.

Figure 2: Spanish Unemployment in the Financial Crisis



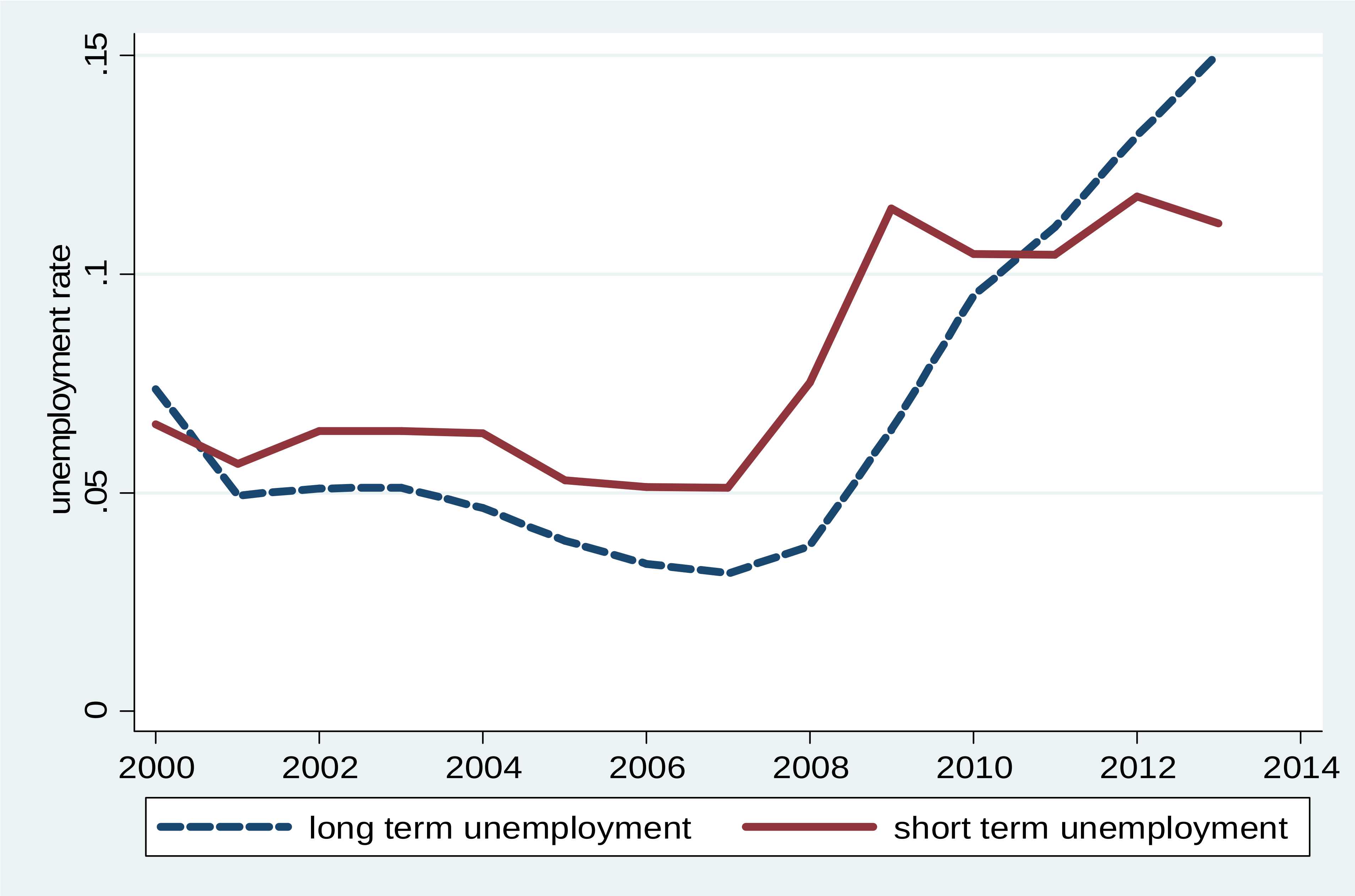
Source: Spanish Labor Force Survey

Figure 3: Changes in Unemployment and the Construction Sector



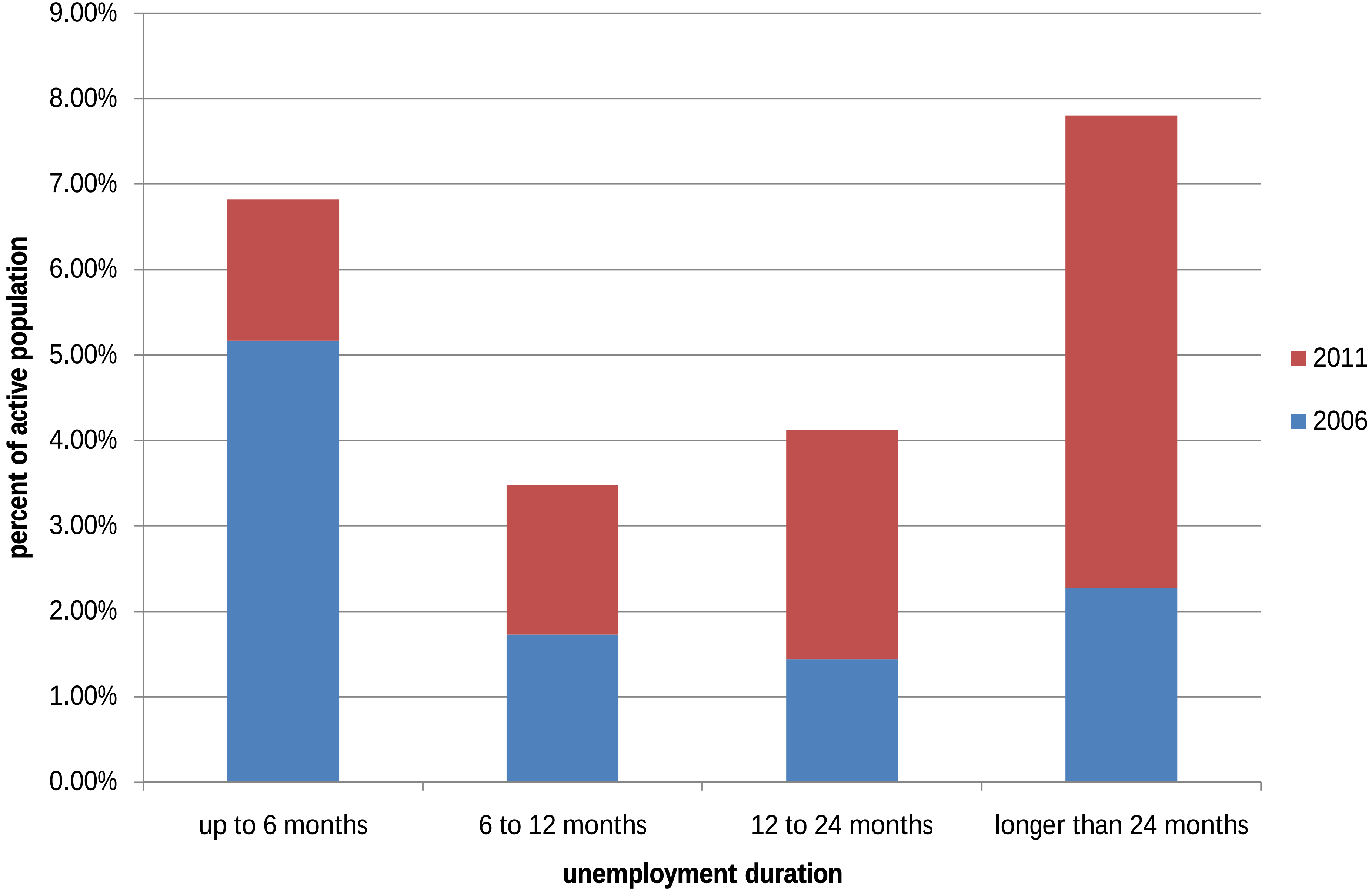
Source: Spanish Labor Force Survey

Figure 4: Short- and Long-Term Unemployment



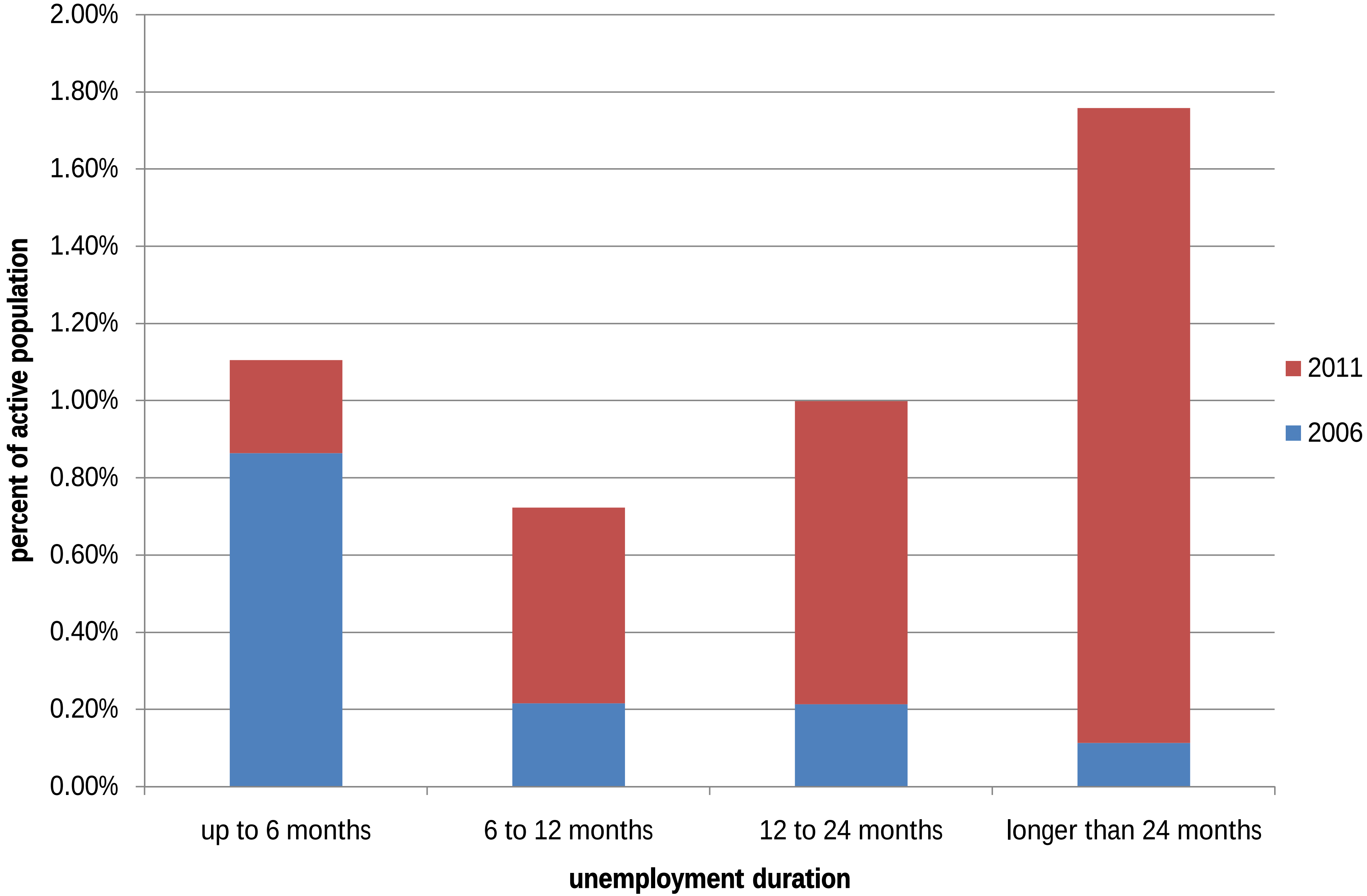
Source: Spanish Labor Force Survey

Figure 5a: Increase in Unemployment Duration (All Individuals)



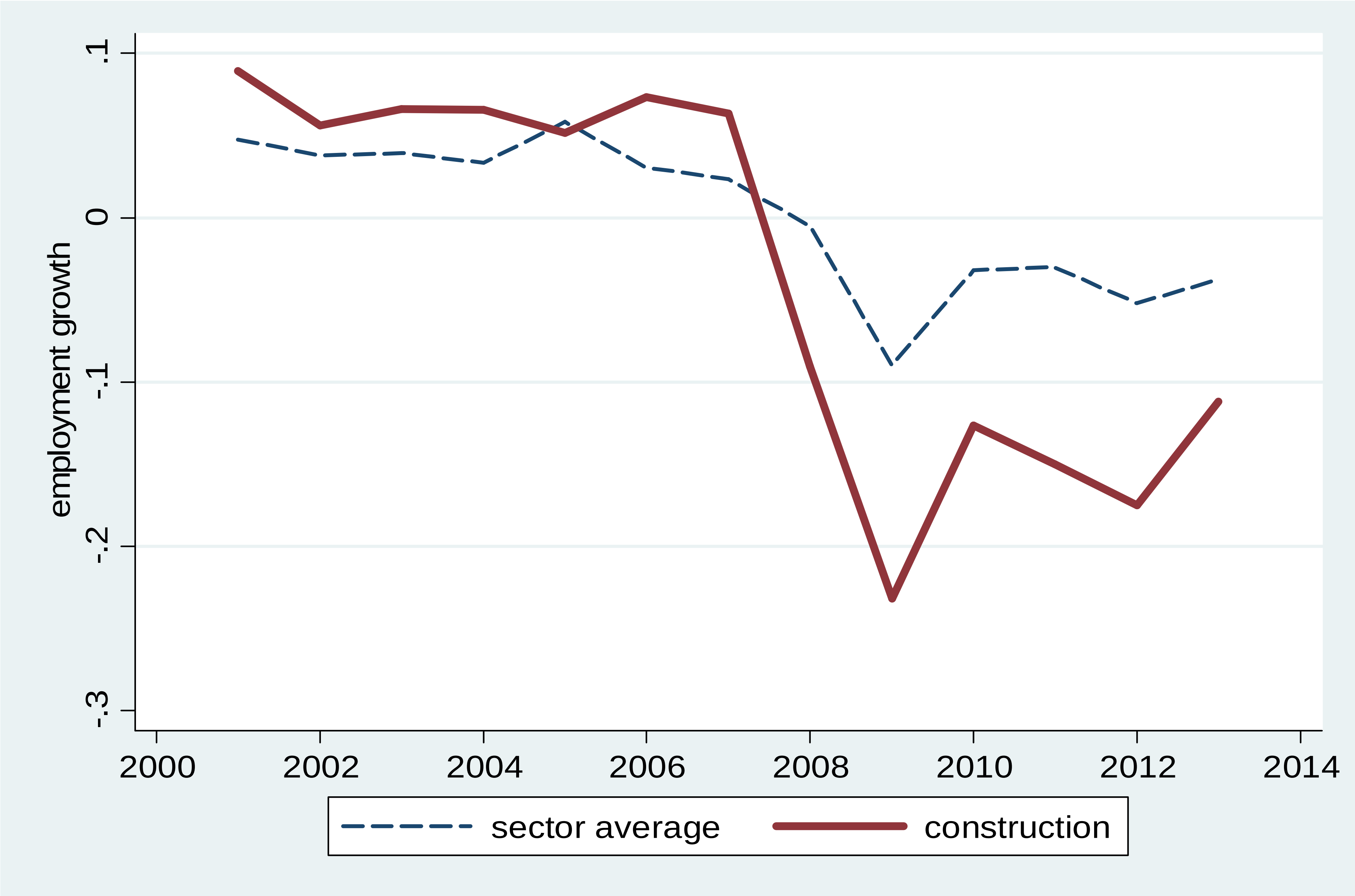
Source: Spanish National Health Survey

Figure 5b: Increase Unemployment Duration (Formerly Employed in Construction)



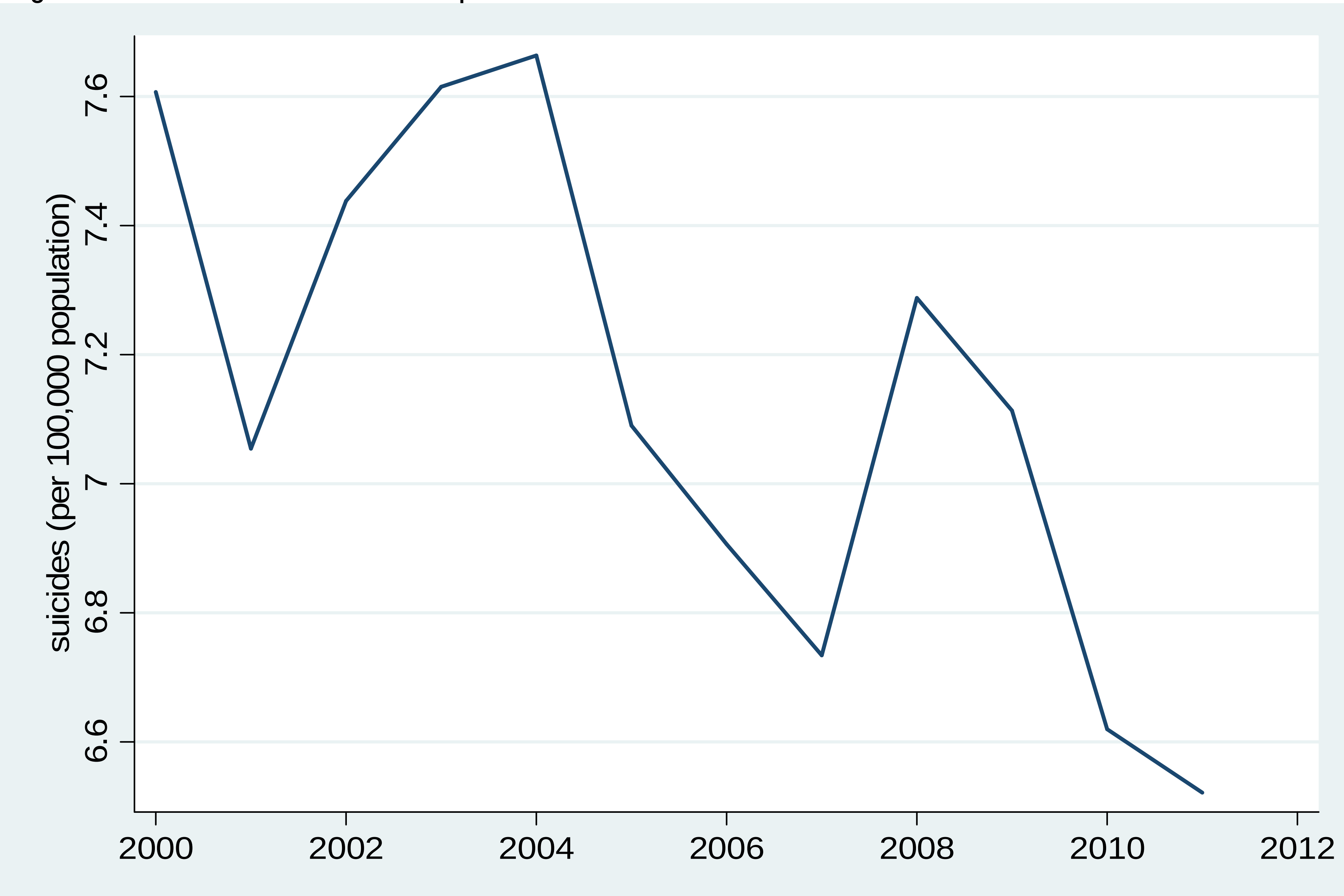
Source: Spanish National Health Survey

Figure 6: Employment Growth in Spain



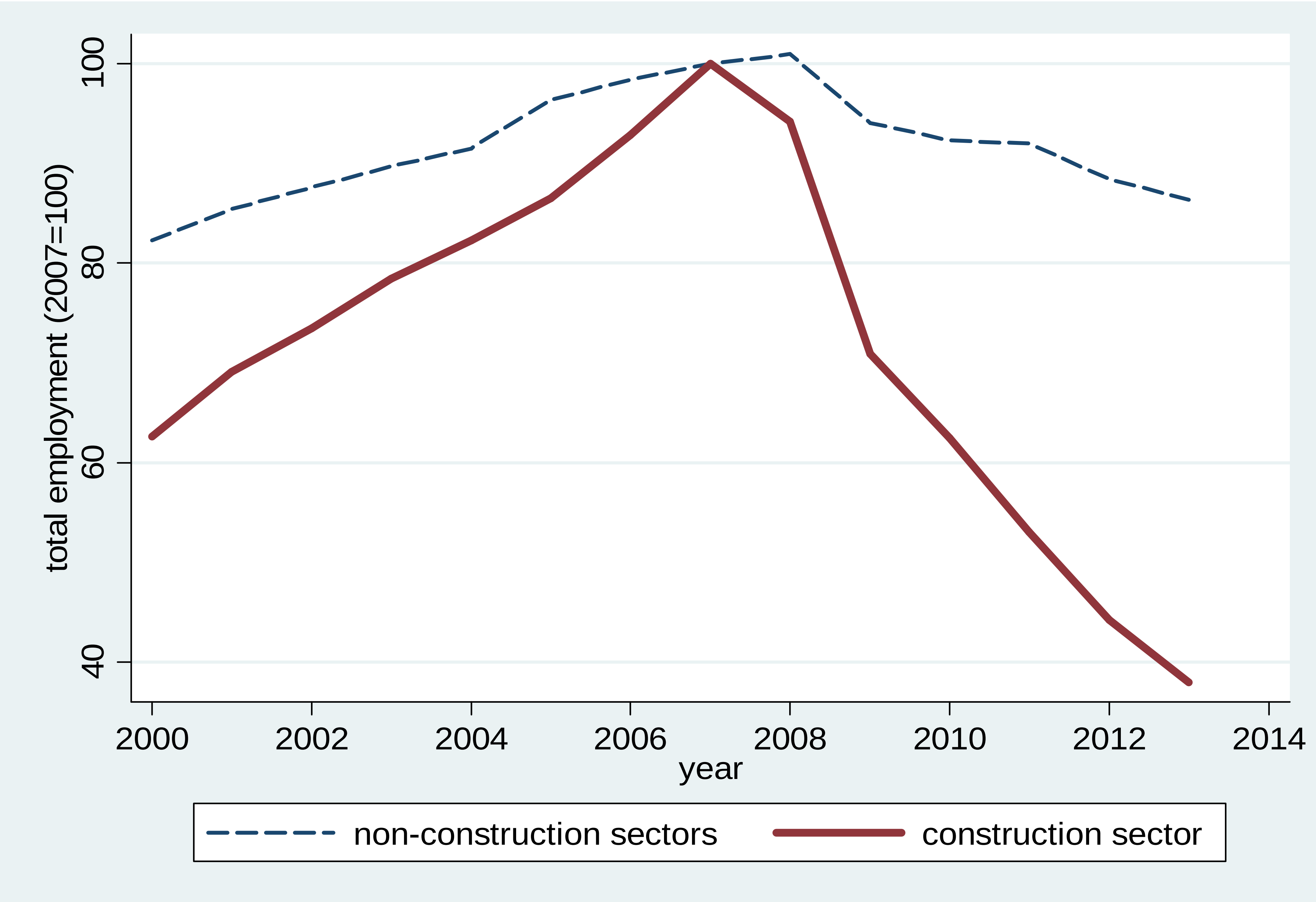
Source: Spanish Labor Force Survey

Figure 7: Number of Suicides in Spain



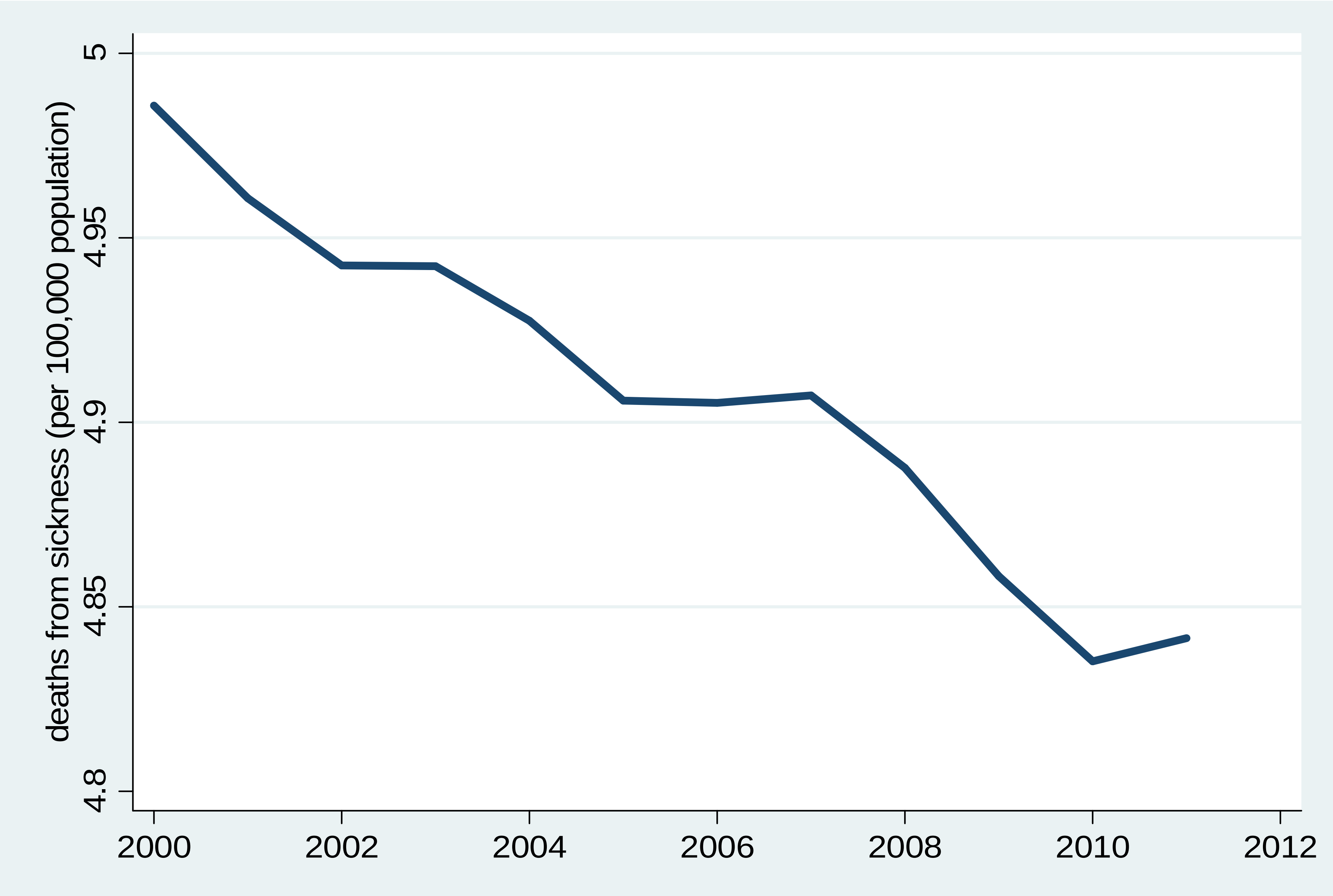
Source: Spanish Statistical Office. Death reports.

Figure A1: Boom and Bust of Employment in the Construction Sector



Source: Spanish Labor Force Survery

Figure A2: Death Rate from Sickness in Spain



Note: Figure shows the sum of deaths from the four main illnesses (cancer, respiratory, infectious and cardiovascular deseases).

Figure A3: Fitted Unemployment Rates in 2006 and 2011