The effect of unemployment spells on subsequent wages in Spain.*

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1 Introduction

This paper is the first of a series devoted to the anatomy of the Spanish labour market. The main motivation is to get an idea about how labor market institutions work their way into unemployment and its structure. Most of the work on the role of labor market institutions focus on cross-country comparisons of aggregate data. In this project, by contrast, we want to retain the idea of comparing countries but to look at microeconomic data instead.

Potentially, labor market institutions affect the anatomy of the labor market in many respects. Firing costs, unemployment benefits, and wage setting institutions have an important impact on the structure of transition rates between employment and unemployment, as well as on the joint process of wages and employment spells for an individual. They also have different

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impacts for different types of workers[1]. This is why we believe that looking at the structure of the labor market for different groups and comparing it with other countries where institutions are different may shed light on the causes of unemployment and on the most relevant mechanisms.

In this paper we look at the impact of unemployment spells on subsequent wages. It is known from the previous literature that in the United States (Ruhm [11], Addison and Portugal [1], Jacobson *et al.* [7]) and Canada (Houle and Van Audenrode [6]) job loss subsequently leads to wage losses of an order of magnitude of 10 to 15 %. Moreover, McLaughlin [10] finds, for the US, a high degree of wage flexibility: he reports that agents frequently take wage cuts whether or not they leave their current employer. Thus, the individual wage distribution is not truncated from below. One may speculate that such wage loss would be distorted by wage rigidities in Europe. It is therefore adequate to study it and compare the results with the US economy.

This is what Cohen, Lefranc, and Saint-Paul [3] have done for the French economy. They find a very similar discount between France and the US, although as the next section makes clear, it does not imply that unemployment benefits play no role. In fact, some rigidities reduce the discount but others increase it. What follows from the model below and from Cohen et al.'s results is that a reduction in unemployment benefits in France would indeed reduce unemployment duration but at the same time would imply large wage losses for displaced workers. That is, if unemployment benefits were reduced to the US level wage losses associated with displacement would fall below the US level because the low arrival rate for job offers tends to reduce the reservation wage.

In our analysis we try and recover the wage loss from unemployment in Spain and see how it is affected by previous unemployment experience, unemployment duration, eligibility for unemployment benefits, and previous wages. We also study its variations across groups. Our main conclusion is that while there is some evidence that labour market rigidities tend to lower it, the wage loss of displaced workers is remarkably high: more than 30 %, that is, twice the equivalent figure for the US and France. Wages in Spain

[1] Carrington [2], for example, finds that more educated and more experienced workers suffer higher wage cuts after unemployment. Cohen *et al.* [3] report a similar finding for France: old educated workers experience the strongest wage losses from displacement. Jacobson *et al.* [7] report huge permanent wage losses for involuntary separations among high tenure workers.

suffer from a serious mismeasurement problem that we do our best to control, so that our results are less robust than the ones that would be obtained with better data sets. However, they indicate a large level of wage flexibility in Spain.

Previous studies were mostly directed at the United States. Addison and Portugal [1] find that, in the US, the wage loss from involuntary displacement is, as it is to be expected, positively affected by the lenght of the unemployment spell as well as occupational and industry shifts. This is consistent with arguments such as depreciation of human capital (Lazear, [8]) or the stigma effect of being unemployed (Heckman and Borjas, [5]): their figures say that a 10% longer spell implies a further wage loss of around 1%. In addition, they also find that, strikingly, wage loss is *negatively* affected by tenure on the predisplacement occupation. Jacobson *et al.* [7], in a study on high tenure workers separations, find that in the case of mass lay-offs, workers *permanently* lose around 25% of their previous wages whereas, in the case of voluntary quits the permanent loss is nearly nought. For Canada, Houle and Van Audenrode [6] find that, wage losses after unemployment notwithstanding, duration of unemployment itself has not the same effect found for the US.

The paper is divided as follows. Section 2 introduces a model of wage rigidities and wage losses. Section 3 and 4 describe the data while section 5 presents our empirical approach to the problem. Section 6 reports and discusses the results. Section 7 concludes. In the Appendix we report the results obtained from several formulations of our basic model.

2 A simple model of labour rigidities and the reservation wage

In this section we study how labor market rigidities affect the reservation wage. One might believe that the reservation wage should be higher, everything else equal, in Europe than in the US, mostly because of more generous unemployment benefits. However, as our analysis shows, there are other effects so that in fact one does not expect the numbers to be that different.

Consider a worker who is looking for a job and who receives job opportunities at a rate of λ jobs per unit of time. Each job is associated to a wage offer which might vary across firms. Call $F(w)$ the cumulative distribution of wage across job offers. Search theory (see Diamond, [4]) show that the worker's decision amounts to estimating a reservation wage w^* and to take any offer above w^*, and reject any offer below it.

The equilibrium value of w^* will be the outcome of two competitive evaluations. On the one hand, accepting a wage offer w immediately ends the quest and raise the current level of revenue that the worker receives. Call c the unemployment benefits received by the worker, the current gain is then simply $w - c$. On the other hand, accepting a wage w forecloses other opportunities that could be offered in the future. Those opportunities, when they are flowing, would yield an additional income worth $\int_{w^*}^{\infty}(w - w^*)dF(w)$ on every period during which the job is likely to be kept by the worker. So the present value of those potential gains must be weighted by a discount factor. Call δ the rate of time preference of the worker and s the separation rate at which a job is ended, one must then weight the preceding integral by $1/(\delta + s)$. But these gains must themselves be weighted by a number which corresponds to the likelihood that such an offer will indeed be channelled to the worker, that is by the job offer rate λ. Bringing these features together, one gets that the equilibrium reservation wage w^*will be a solution to :

$$w^* - c = \frac{\lambda}{\delta + s} \int_{w^*}^{\infty}(w - w^*)dF(w)$$

In which, λ and s stand for the offer and separation rate per unit of time, and δ stands for the rate of time preference. The left-hand side is an increasing function of w^* while the right-hand one is a decreasing function, so that there is a unique equilibrium. If one neglects for the time being the role of c, unemployment benefits, and of δ the time preference parameter, one gets that the reservation level w^* is only a function of λ/s which is the ratio of the job offer rate to the job separation rate. One key difference between Europe and the US is that both λ and s are far smaller in Europe than in the US, while the ratios between the two are similar across both sides of the Atlantic. Two countries with similar λ/s ratios would then deliver identical reservation wages. The intuition is simply the following. European workers should accept lower wages when they are offered one because those offers are rare (compared to the US). On the other hand, because they are likely to keep the job longer, European workers are also more demanding: they do not want to get stuck with a low wage forever. Such is not the concern of a US worker who can simultaneously afford to reject a bad job because other offers will be forthcoming, but who do not mind either because it will not last anyway...

When unemployment benefits and time preferences are plugged to the analysis, two additional effects tilt the picture. Higher unemployment benefit (as in Europe) raise the European reservation level (it is less costly to wait). On the other hand, taking account of time preference will lower the reservation level of the country in which the job offer rate is the lowest: on average one has to wait longer before another offer is made and although the next offer will last longer this tilts the decision towards accepting more often a job. Bringing these two pieces together, one gets an ambiguous result: depending on the relative strength of the time preference factor relatively to the unemployment benefit factor, wages could be more "flexible" in either country.

This model determines the reservation wage but has nothing to say about the wage loss of displaced workers. It predicts that the wage distribution of new jobs is the same as the wage distribution of existing jobs. So the wage loss is on average zero.

The model can be transformed into a model of the wage discount if expanded in one direction: job promotion. When workers take an offer, this is not the end of the story: they may keep climbing up the pay ladder. In order to model this process, we follow Lefranc [9] and assume that once unemployed workers have accepted an offer, they can get another offer, drawn from the same distribution, with the same arrival rate h. For simplicity we assume they accept this offer if and only if it pays more than their existing wage. Once they have done so they won't get any other offer, unless they become unemployed, in which case their search process starts again. Let V_u, $V_1(w)$, and $V_2(w)$ be the value of being unemployed, the value of being employed with wage w before the second offer has arrived, and the value of being employed with wage w after having accepted the second offer, respectively. We assume wage offers are uniformly distributed over $[1-\sigma, 1+\sigma]$.

Then in steady state we must have:

$$rV_1(w) = w + s\left(V_u - V_1(w)\right) + \frac{h}{2\sigma}\int_w^{1+\sigma}\left(V_2(w) - V_1(w)\right)dw$$

$$rV_2(w) = w + s(V_u - V_2(w))$$

$$rV_u = c + \frac{h}{2\sigma}\int_{w^*}^{1+\sigma}\left(V_1(w) - V_u\right)dw$$

$$V_1(w^*) = V_u,$$

where w^* is the reservation wage. These equations can be solved numerically, yielding a reservation wage. Then one can compute the number of workers in each state by solving the following flow equilibrium equations:

$$hu\frac{1+\sigma-w^*}{2\sigma} = s(n_1+n_2)$$

$$hu\frac{1+\sigma-w^*}{2\sigma} = sn_1 + hn_1\frac{1}{1+\sigma-w^*}\int_{w^*}^{1+\sigma}\frac{1+\sigma-w}{2\sigma}dw$$

$$1 = u + n_1 + n_2,$$

where u is the unemployment rate, n_1 the fraction of the workforce in state 1, n_2 the fraction of the workforce in state 2. The first equation states that inflows into unemployment equal ooutflows, while the second one states than inflows into state 1 equal outflows.

Next, the steady state distribution of wages in state 2 can be computed using a similar flow equilibrium condition:

$$sn_2\varphi(w) = n_1\frac{w-w^*}{1+\sigma-w^*}\frac{h}{2\sigma},$$

where $\varphi(w)$ is the density of state-2 workers earning between w and $w+dw$. The LHS is the outflow from this group, while the RHS is the inflow: workers in state 1 will accept this offer if they initially earn less ($n_1 \frac{w-w^*}{1+\sigma-w^*}$ people), they receive an offer with flow probability h, and wage density $1/(2\sigma)$. As for the density of state-1 workers, it is simply uniform over $[w^*, 1+\sigma]$.

The wage discount is then computed, once the model has been solved, by comparing the average wage of first offers to the average wage economywide.

With $r = 0.05$, and $c = 0.6$, $\sigma = 0.5$, $h = 0.6$, $s = 0.075$ for Europe, we get a wage discount of -9.05 %. For the U.S., with $c = 0.25$, $\sigma = 0.7$, $h = 3.2$, $s = 0.36$, the implied discount is -9.43 %. Note that the discount would be reduced to -7.97 % in the U.S. if it had the same unemployment benefit level as Europe, while it would increase to -11.3 % if the U.S. has the same hiring and separation rates as France. Thus we see that the similar discounts are the outcome of offsetting effects. Note also that the model matches well the order of magnitude of the discount for France and the US estimated by CLSP.

3 Description of the data

The dataset we use for this study is the Encuesta Continua de Presupuestos Familiares (henceforth, ECPF), a survey of family expenditures performed on a quarterly basis by INE. The basic unit of the survey is the household and each household is followed up to a maximum of 8 quarters.

Within each household, information about individual characteristics, employment status and sources of earnings is available for its different members (head, spouse, others)[2]. Some qualifications, though, become necessary.

As to the sources of quarterly earnings of each member, we have a quite clear classification along the following lines: self-employment, employement, rentier, pensions and unemployment benefits. Along with that, we have information on the total inflows of money during the past quarter accounted for by any source. These inflows are considered as net of all taxes and, broadly speaking, Social Security contributions.

[2]As it will be explained below, availability of information about individual characteristics and current employment status is limited for those agents who are not heads of a household.

As to employment status, it only refers to the week preceding the survey. Thus we are not able to tell anything about, say, intra-quarter unemployment spells. As it will be explained below, we try to overcome this pitfall by means of alternative wage definitions.

Workers are assigned to one of four educational categories: LOW corresponds to workers with no schooling, MEDIUM education stands for workers who have completed primary instruction. HIGH education are those workers who have at least completed secondary education and VERY HIGH education is workers who at least completed university.

Compared with CLSP, we have a finer classification at the low end of the educational ladder. They do not distinguish between workers with no schooling and those with some basic education, and include them in the LOW education group. Our HIGH education group includes all those workers who have completed some secondary instruction whereas in CLSP this group only includes workers with a baccalaureat (which correspond more or less to the upper part of our HIGH education group). As to the VERY HIGH education group, it accounts for more or less the same education levels in CLSP and in our study.

The sample we use in all our regressions only includes full-time workers. We achieve this by simply dropping all those agents who declared at least once, while in the survey, to have worked less than 1/3 of the normal daily working time. We are aware that this also drops many observations for which the part-time hypothesis is not at all justified (e.g. people on illness leave, temporary lay-offs, etc.). Still, we assign a higher cost to having people with low attachment to the workforce in our sample. We also try to dispose of those observations that are likely to be associated with within-quarter (non observable in the data) unemployment spells. Therefore, we drop all those observations that report, at time t, employment at both $t-1$ and t along with unemployment benefits payments at time t.

We also control as much as we can for heterogeneity in the sources of earnings. Namely, we introduce two dummies identifying, respectively, self-employed (SE) and people who are likely to have a side activity ($SELF\ EMP$).

3.1 Measuring wages

Given the fact that agents' declared employment status only refers to the week preceding the survey whereas information about inflows of money refers to the whole past quarter, one cannot directly match employment status at time t with declared incomes in the same period. In other words, we do not observe the wage (in the sense of the price of the individual's time), but just the income over a 3-month period where we have no information on the worker's activities but for the last week.Therefore we built the following wage definitions that, in different ways, take this peculiarity into account. These definitions exploit the temporal structure of the survey and merge information concerning the same individual at different periods.

Definition 1: if agent (employed at t) was unemployed at time $t-1$ AND employed at $t+1$ then his wage at time t is defined as what he declared as income from employement at time $t+1$. On the other hand, if he was employed at $t-1$ then wage at time t is what he declares as income from employment in period t. If he is employed at t but unemployed at both $t-1$ and $t+1$, then the wage is not available. Hence:

$$wage1_t = \left\{ \begin{array}{cc} dec\_wage_{t+1} & \text{if unemployed at } t-1 \text{ and employed at } t+1 \\ dec\_wage_t & \text{if employed at } t-1 \\ NA & \text{if unemployed at } t-1 \text{ and } t+1 \end{array} \right\}$$

where dec_wage_t is what is found in the dataset at time t and $wage1_t$ is our corresponding definition 1. This definition partially solves the problem of individuals that do not earn a full 3 month wage over period t because their unemployment spell reported at $t-1$ ended during t . Our definition makes sure that the worker was already employed at the end of the quarter preceding the one where the wage is measured. Implicit in this definition, there is an assumption on the stationarity of wages between quarters.

Definition 2: if agent is unemployed at $t-1$ and, in that period, ONLY declared earnings from unemployment benefits (b_{t-1}) then wage at t is built as follows:

$$wage2_t = \frac{dec\_wage_t}{1-x} \qquad x = \frac{b_t}{b_{t-1}}$$

where b_t is the declared unemployment benefit received during period t. If agent was employed both at $t-1$ and t then his $wage2_t$ is built as in definition 1. The aim of this second definition is to take into account those unemployment spells that do not appear in the survey (within the quarter spells). We do that by building the wage that the agent would have earned if he had been always employed during the quarter. The measure of the lenght of this intra quarter unemployment spell is x, that is, we assume that the worker was fully unemployed during quarter $t-1$ and that the benefit payment per unit of time spent in unemployment is the same across the two quarters, which allows to compute the time spent in unemployment during period t.

These two definitions clearly reduce the sample size. Moreover, they do not span the same space. Hence, we also merge them into a third one giving priority to definition 1.

3.2 Observability of the causes of job loss

One shortcoming of our dataset is that there is no question about the causes of job loss. Therefore, we cannot limit ourselves to workers having lost their jobs for truly exogenous reasons. This may generate biases in our estimate of the wage discount if those who lose their jobs are selected according to characteristics correlated with the error term in a wage equation (such as unobserved ability). One could potentially reduce this bias by taking advantage of the panel dimension of the dataset. However, this is likely to generate other problems as the non observability of the wage variable during periods of unemployment prevents from taking first differences.

3.3 Availability of variables depending on family status

ECPF being a consumption and expenditures survey, information on individual characteristics is overall quite limited. The main drawback is that it depends on family status. Starting from the head of the household, information concerning individual characteristics shrinks as we consider other members. The following table reports how individual characteristics are available depending on the individual's status in the family.

	Sex Age	Income Source	Employment Status	Education
Head	X	X	X	X
Spouse	X	X	X	
Others	X	X		

This implies that our sample only includes heads of households (we always include education in our regressions). A shortcoming of this is that the conclusions we draw are very reliable for the males in the core age group, whereas they can be somewhat misleading for other sex*age cells of our classification due to limited group sample size.

4 Empirical Strategy

Our empirical strategy is the same as in the literature: we estimate a standard wage equation which explains log wages by worker characteristics: age, sex, education. Namely:

$$Y_{i,t} = \alpha + X_{i,t}\beta + D_{i,t}\gamma + u_{i,t}$$

where $Y_{i,t}$ is quarterly earnings of individual i at time t. $X_{i,t}$ is a collection of dummies for individual characteristics and $D_{i,t}$ is a collection of dummies representing individual's employment status in previous periods.

The effect of unemployment on wages is estimated by adding a dummy equal to one if the individual has gone through unemployment. Namely, we define it as:

$$UNEMP_t = \begin{cases} 1 \quad if \quad unemployed \quad at \quad t-1 \\ 0 \qquad\qquad otherwise \end{cases}$$

The coefficient on the unemployment dummy, if negative, tells us how much one loses in one's next job if one has gone through unemployment. We use two specifications of the wage equation: in one of them we include the log of the past available wage as an explanatory variable, in the other we do not. Theory tells us that if the adequate variables are included in the regression, past log wages should not come out significant. However, if there are omitted variables such as unobservable ability, then inclusion of the past wage proxies for such omitted variable, which reduced the associated bias in the estimated wage discount. We estimate our equation by pooling all our observations. Wages may be systematically correlated with calendar time or the business cycles. For example, in the sample, employment spells following spells of unemployment are likely to occur at dates systematically correlated with the business cycle. To eliminate these potential sources of bias we include year dummies and seasonal dummies, as well as dummies representing the date of the last wage whenever that variable is included. All systematic variations in wages due to inflation, growth, business or seasonal cycles are picked up by these dummies.

In order to sort out the effect of unemployment from the effect of non-employment, we also include a dummy for having been out of the labor force. We also want to analyse how the wage discount depends on worker's characteristics. We therefore cross worker's characteristics with the unemployment dummy ($UNEMP_t$) and the one for having been out of the labour force in the previous period (OLF_t).

We then perform three exercises. First, we want to capture how the structure of the past unemployment spell affects the wage discount. Therefore, we include a dummy that says whether the agent is a long term unemployed or not. This dummy is defined as follows:

$$LONG \quad UNEMP_t = \begin{cases} 1 & if \quad UNEMP_{t-i} = 1 \quad i = 0,1,2 \\ 0 & \qquad otherwise \end{cases}$$

We also include a dummy representing the total share of time spent in unemployment, defined in the following way:

$$STUN_t = \frac{\sum_{s=t-j}^{t-1} EMPL_s}{j}$$

where $EMPL_s = 1$ if employed at s and 0 otherwise and $j+1$ is the number of periods the agent has been in the survey as of time t. This allows to capture the cumulative effect of *all* past unemployment spells, rather than just the last one, thus allowing to say something as to whether the labour market has a "long memory". Similarly, we define a dummy representing the total share of time spent out of the labour force ($STOLF$). Second, we want to see whether institutional wage rigidity (such as minimum wages and collective agreements) prevents the reservation wage from dropping at the low end of the wage distribution. To capture that we add a quadratic polynomial in the last available wage crossed with the unemployment dummy. This allows the wage discount to vary in a rather arbitrary way with past wages. If wage rigidity matters we should expect our regression results to tell us that the discount is lower at lower past wages. Finally, we want to know whether unemployment benefits bid up the reservation wage, thus preventing the wage discount from falling. To do that we add a dummy controlling for eligibility for unemployment benefits. We use two slightly different definitions for this dummy, both of which have their weaknesses and strengths.

The first formulation is the following:

$$ELIG_t^1 = \begin{cases} 1 \quad if \quad b_{t-1} > 0 \quad and \quad UNEMP_t = 1 \\ 0 \qquad\qquad otherwise \end{cases}$$

We say that an individual is eligible at time t when, at $t-1$ he both declares himself unemployed and among his earnings we find unemployment benefits payments.

The second definition is as follows:

$$ELIG_t^2 = \begin{cases} 1 \quad if \quad b_t > 0 \quad and \quad UNEMP_t = 1 \\ 0 \qquad\qquad otherwise \end{cases}$$

Here we are saying that an individual qualifies for unemployment benefits when, *after an unemployment spell* ($UNEMP_t = 1$), he has received some payment for unemployment benefits ($b_t > 0$).

Given the problems we have in matching earnings with individual status, this second definition is likely to be picking up all the observations for which the current wage is mismeasured. On the other hand, it yields a somewhat better match between status and earnings, on the grounds that there is some lag in UB payments and that the employment status refers to the last week of the corresponding quarter. The first definition misses slightly this feature of the data but does not introduce a bias toward mismeasured observations.

5 Results

5.1 Wage losses in various groups

The regression results were quite similar across our three wage definitions, which suggests that the wage measurement problem might not be too severe.

Table 1 reports the basic regression results for our preferred wage definition. We report the estimates with inclusion of the last wage; estimates without inclusion of the last wage differ substantially and turn out not to be very robust; they are reported in the appendix.

Table 1: Regression results for three alternative models

Variables	All Groups	Group Dummies	2 Education Levels	
Intercept	(**) 5.08	(**) 5.08		(**) 4.48
Past Wage	(**) 0.6	(**) 0.6		(**) 0.635
Age1	(**) -0.15	(**) -0.15		(**) -0.16
Age2	-0.003	-0.004		0.00
Sex	(**) 0.16	(**) 0.16		(**) 0.143
High Ed.	(**) -0.17	(**) -0.17		
Mid Ed.	(**) -0.25	(**) -0.25	Low Ed.	(**) -0.147
Low Ed.	(**) -0.36	(**) -0.36		
Unemp	(**) -0.385	(**) -0.34		(**) -0.57
OLF	(**) -0.383	(**) -0.28		(**) -0.3
Sex*Unemp		(*) 0.112		(**) 0.14
Sex*OLF		(**) 0.19		(**) 0.22
Age1*Unemp		0.146		0.14
Age1*OLF		0.21		0.16
Age2*Unemp		0.03		0.056
Age2*OLF		0.04		0.03
HE*Unemp		-0.18		
HE*OLF		-0.02		
ME*Unemp		-0.048	LE*Unemp	(**) 0.12
ME*OLF		-0.11	LE*OLF	-0.06
LE*Unemp		-0.04		
LE*OLF		0.06		

NOTE: (**)=significant at 5%; (*)=significant at 10%

The first column of table one reports the regression results assuming the same discount for everybody. The magnitude of the wage loss, as implied by Table 1, is quite large. The estimated coefficient is -0.385, which means a wage loss on average equal to 32 %. This is a far bigger number than found in the previous literature on France and the US.

When the wage loss is allowed to vary across groups by including group dummies, the following pattern is found (column 2 of table 1): the wage loss is lower by 11 % for men than from women, suggesting that they suffer less from unemployment spells, perhaps because they are more picky in choosing their next jobs, or because they are more likely to be covered by collective agreements. Young agents also have a lower wage discount, while the dependence in education is non monotonous. It implies that the high education group suffers from a wage loss eighteen percent higher than other educational groups, that include both the most educated and the low educated.

Table 1 also suggests that spells out of the labor force have similar effects on wages as spells of unemployment, although the specific coefficients may vary from group to group. Column one suggests a wage loss almost identical indeed.

The third column of table 1 reports the regression results when the workforce is split in only two educational groups. That makes our results more comparable with those of CLSP. The results confirm the finding of a high discount, and imply that the low education group has more rigid wages than the high education one.

Table 2 summarizes the wage discount found for each group, according to the regression results of table 1. The first panel uses four educational categories, the second one just two. In the second panel our results are compared with the CLSP findings for France and the US. As we see the discounts are much larger in Spain, and they are increasing with age and education[3], while there is no systematic pattern in the two other countries

[3]Although remember that when four education groups are considered this monotonicity disappears.

Table 2a: Percentage change in wage for previously unemployed workers

Age	Education			
	Low	Medium	High	Very High
16-24	-12.9	-12.4	-23.6	-8.1
	-21.3	-21.7	-31.7	-17.8
25-49	-21.6	-22	-31.9	-18.2
	-29.9	-30.3	-39.1	-26.8
50-	-23.9	-24.3	-33.9	-20.6
	-32	-32.3	-40.9	-29.0

First row in cell is Males
Second row is Females

Table 2b: Wage discount for previously unemployed workers

	Education					
	Low			High		
Age	Spain	France	USA	Spain	France	USA
16-24	-15.6	-7.3	-44.9	-25.1	-15.3	-7.2
25-49	-22.8	-13.2	-11.0	-31.6	-9.3	-5.2
50-	-26.6	2.1	0.1	-34.9	-30.7	-2.7

Results for France and USA are as
Table 7 in Cohen, Lefranc and Saint-Paul (1997).
LOW includes low and medium education workers;
HIGH includes high and very high education workers.
Group 25-49 is males. Other groups are both sexes for
France and US, while for Spain only males

One aspect of our regressions is that the wage discount is not allowed to vary freely across groups since group effects are captured by dummies representing age, education and sex rather than by dummies representing any cell. For that reason we have re-run one regression by cell. Table 3 reports our basic results, while table 4 reports our finding when only two educational groups are used and compares them with CLSP.

Table 3: Wage discount after unemployement.

MALES

	Education			
Age	Low	Medium	High	Very High
16-24	NA	29.7	(*) -19.7	NA
25-49	(**) -32.9	(**) -27.3	(**) -42.8	-13.9
50-	(**) -25.9	(**) -32.9	(**) -42.8	NA

FEMALES

	Education			
Age	Low	Medium	High	Very High
16-24	NA	(*) (B) 118.1	(**) -72.2	NA
25-49	-18.1	(**) -27.3	(**) -33.6	(**) -75.5
50-	NA	NA	NA	NA

(B) = multicollinearity in the cell.

NA == UNEMP=0 in the cell

Regressions are run by cell.

The results are somewhat different from table 2 and suffer from sample problems for some cells. We still find wide variation across groups, however, the difference between females and males seems to come only from the highest education group where the discount is now insignificant for men and unplausibly high for women. And for other groups, we if anything find a lower discount for women than for men and the coefficient is often insignificant for women. The pattern of wage discounts according to education is confirmed for the male core age group. The highest and medium educational level have the most rigid wages, perhaps because the first group is likely to be "picky" while the second is likely to be made of "insiders".

For people aged more than 50, the wage discount is monotonously increasing with education; this seems to indicate that these agents lose a lot of human capital when losing their jobs, more so when more educated.

Finally, we fail to find a significant discount for the young males, suggesting that this group has a rigid wage formation despite being less protected by labor market institutions than other groups.

Table 4 compares our results with the ones in CLSP. To do so we again re-run the regression with just two educational groups. The pattern of wage loss is quite different between the two countries. In Spain the low education group is always more rigid, whereas in France the reverse holds for the core age group. In Spain the discount is increasing with age, whereas in France it first falls and then rises for the highly educated, with a reverse pattern for the less educated.

Table 4: Wage discounts. Two education levels

	Education					
	Low			High		
AGE	Spain	France	USA	Spain	France	USA
16-24	33.6	(*) -7.3	-44.9	-18.9	-15.3	-7.2
25-49	(**) -29.5	(**) -13.2	(**) -11.0	(**) -39.3	-9.3	-5.2
50-	(**) -32.3	2.1	0.1	(**) -46.7	(**) -30.8	-2.7

France, USA is Table 7 in Cohen, Lefranc and Saint-Paul (1997).
LOW education includes low and medium education workers;
HIGH includes previously high and very high education workers

Given the discrepancies between the results in table 2 and those in table 3 we have to exert our judgement to draw conclusions. Let us spell them out.

1. The wage loss of displaced workers in Spain is large, larger than in France or the U.S. For the core male age group, it ranges from 15 % ($e^{-0.15}$)to 43 % ($e^{-0.56}$)

2. There is wide variation of the wage discount across age, education, and sex.

3. Although a regression that constrains this difference to be equal across education and age groups indicates the contrary, it appears that these results are due to outliers in the most educated group. The wage loss of women is *overall lower than for men: 34 % instead of 43 % for the middle-aged, high education group and 18 % instead of 33 % for the low education group.*

4. There is some evidence of a lower wage discount for the 16-24 age group than for the rest of the population. In a two-educational group regression the wage discount is increasing with age for both educational groups, contrary to what has been observed in France.

5. The wage discount varies non-monotonically with education for the core age group. The medium and very high educated males have the lowest discounts, while the high and low educated have the highest ones. This is consistent with the view that the most educated are more "choosy", while the medium educated are more protected by institutions. At coarsere aggregation levels (2 groups), however, the discount is increasing with education.

6. The wage discount is increasing with education for the workers aged more than 50, suggesting a loss of human capital that increases with education.

7. Spells out of the labor force seem to have similar consequences on subsequent wages as spells of unemployment.

5.2 Institutions and unemployment duration

We now extend our regressions by adding variables that capture the impact of labour market institutions on the wage discount, in the light of the model exposed in section 1.

Table 5 reports regression results when one includes variables that allow the wage discount to vary with unemployment duration, past unemployment spells, eligibility for unemployment benefits, and the past wage. Moreover, the eligibility dummy we use here is $ELIG_t^1$. Results for the alternative definition turned out to be strongly affected by the mismeasurement bias. Again, the last wage was included in all regressions and regressions without the last wage are reported in the Appendix.

Table 5

	ADDITIONAL VARIABLES		
VARIABLES	Duration	Elig.	Past Wage
Unemp	(**) -0.3	(**)-0.34	(**)20.5
Sex*Unemp	0.1	0.084	(*) 0.11
Age1*Unemp	0.15	0.124	0.09
Age2*Unemp	0.03	0.014	-0.02
HE*Unemp	-0.18	(**) -0.264	(**) -0.32
ME*Unemp	-0.05	-0.13	(*) -0.21
LE*Unemp	-0.04	-0.11	(**) -0.32
Long Spell	0.1		
STUN	(**) -0.1		
Eligibility		0.16	
Past Wage*Unemp			(**) -2.94
SQR(Past Wage*Unemp)			(**) 0.01

NOTE: (*) : significant at 10 % (**): significant at 5 %

The first column report regression results when variables capturing unemployment history are crossed with the wage discount. We added one dummy that is equal to one if the last unemployment spell was "long" ($LONG\ UNEMP$), and another ($STUN$) that allows for an effect of unemployment spells previous to the last one. It is equal to the share of time spent by the worker in unemployment, while in the panel. As can be seen, $STUN$ is negative and significant: having spent more of one's life in unemployment reduces the wage that one can get. The order of magnitude of the coefficient is 5-10 %, meaning that somebody who spent half his life in unemployment earns, everything else equal, 2 to 5 % less.

As for the duration of the last spell, it turns out to be not significant at customary confidence levels. This result, though, could be affected by the structure of the dataset we use. The dummy equals 1 when the agent was unemployed at (t-3) and has been unemployed all the time until (t-1). Since the regressions include past wages and since we only observe agents for at most 8 quarters, we are biasing the sample towards those workers with high attachment to the workforce. If this is not the case, then it seems that the market only looks at the overall time spent unemployed ($STUN$) rather than at the duration of the last spell [4] The second column reports the results when a dummy for eligibility to unemployment benefits was included. It turns out to be strongly significant and implies a wage around 17% higher when the worker is entitled to these benefits. The third column is the regression when the last wage is crossed with the unemployment dummy. We included both the last wage and its square. Table 5 indicates that there is a significant variation of the wage loss with respect to the previous income of the worker. In order to get a better grasp at that variation, figure 1 plots the dependence of the wage discount with respect to the wage. It implies a higher discount at higher wages, suggesting that some sort of wage rigidity is at work.

6 Conclusion

The motivation of this paper was to assess the degree of wage rigidity and its causes by looking at the wage loss of workers who go through unemployment, and at its determinants.

Our main result is that the wage loss of workers who go through unemployment is considerably larger in Spain than in either France or the U.S. We have done our best to construct our variables so as to limit measurement problems. Still, it is still possible that our results are due to mismeasurement because of the poor quality of the data. In particular, there is no way to check whether the individual is indeed employed full-time in his next job or to infer the causes of the dismissal. Both problems may lead to too high a wage discount relative to comparable studies.

The pattern of wages varies across age, sex and education groups. These variations are quite large but many of them are not very robust. However, the discount seems to be increasing in age, and in education for older workers. It has an inverted N-shape for the core male age group. When two education groups are used, it is overall increasing with education. The dependence in education may be interpreted as evidence for the role of "insiders", but the dependence in age seems to point towards the other conclusion.

We find some evidence that past employment history affect the wage discount: workers who have spent a greater share of their time in unemployment

[4] Another problem could be that, due to the structure of the dataset, STUN and LONG UNEMP basically span the same space. Recall also what has been said about how wages were defined and the possible drawbacks.

have a greater wage loss.

As for institutions, we find strong evidence that eligibility for unemployment benefits makes workers more "choosy": the wage loss experienced by such a worker is around 17% lower. On the other hand, the discount is lower at low previous wages, which suggests that there is some role for minimum wages and collective agreements. despite the fact that these rigidities seem to work in the expected direction, the overall picture is a market where workers experience considerable wage losses, greater than in France or the United States. This remains somewhat of a puzzle, although we have seen in section 2 that the sluggishness of the labor market itself tends to pushes the reservation wage downwards.

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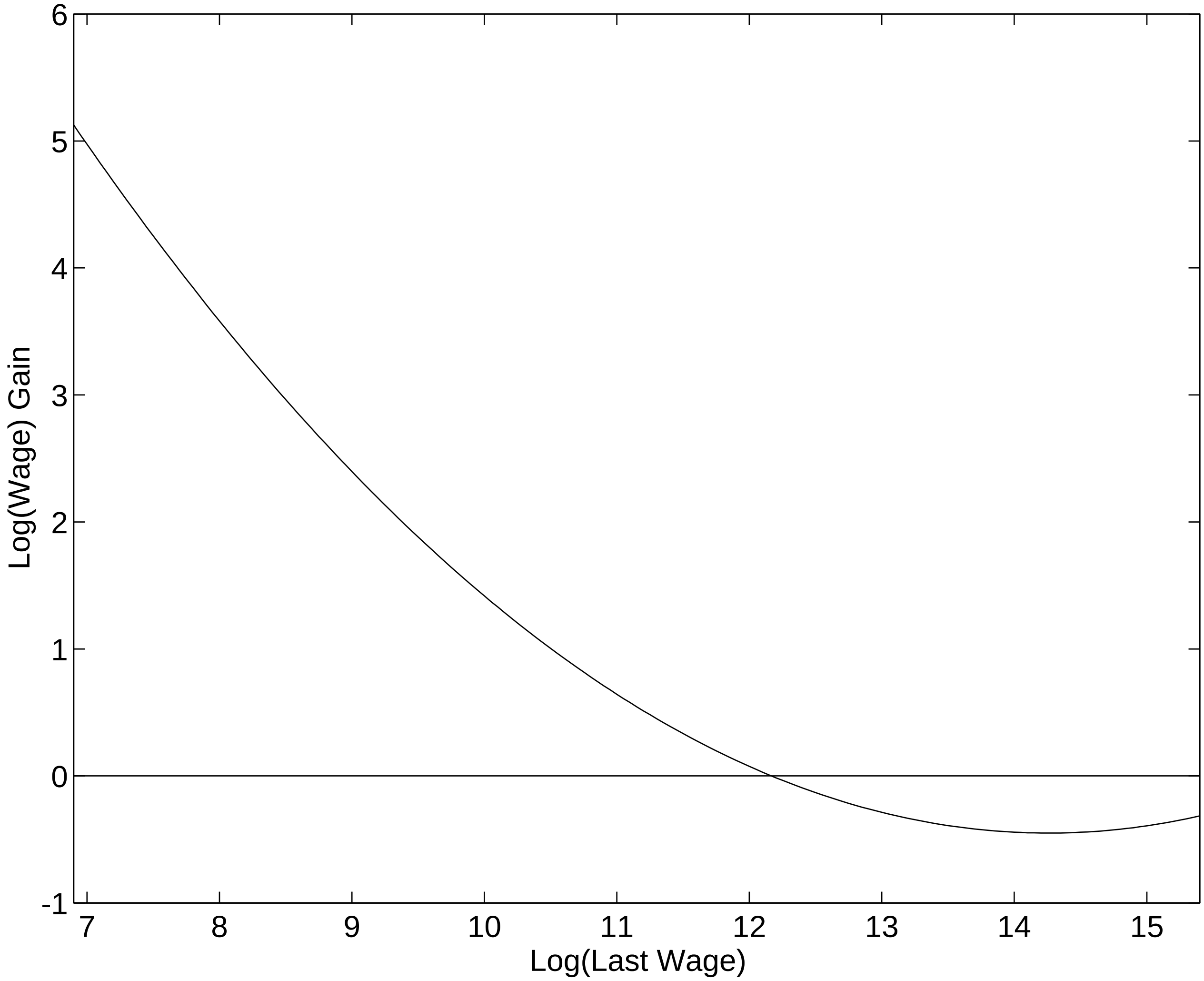
Figure 1: Wage Gain for Displaced Workers



Variable	**Estimate**	**T-Statistic**
INTERCEPT	5.08	105.1
LOG(LAST WAGE)	0.59	161.6
AGE1	-0.156	-11.8
AGE2	-0.004	-1.08
SEX	0.156	27.76
HIGH	-0.167	-32.314
MEDIUM	-0.254	-49.215
LOW	-0.359	-53.279
UNEMP	-0.343	-2.59
OLF	-0.279	-2.08
SELF EMP	0.348	29.148
SE	-0.413	-28.74
SEX*UNEMP	0.112	1.688
SEX*OLF	0.192	2.8
AGE1*UNEMP	0.146	1.447
AGE1*OLF	0.21	1.262
AGE2*UNEMP	0.03	0.66
AGE2*OLF	0.04	0.574
HIGH*UNEMP	-0.184	-1.602
HIGH*OLF	-0.025	-0.192
MEDIUM*UNEMP	-0.048	-0.439
MEDIUM*OLF	-0.11	-0.945
LOW*UNEMP	-0.043	-0.374
LOW*OLF	0.064	0.473
UNEMP*SELF EMP	-0.72	-13.276
OLF*SELF EMP	-0.55	-8.229
R^2	0.65	

Table 1: Model includes last available wage

Variable	Estimate	T-Statistic
INTERCEPT	12.55	1013.013
AGE1	-0.28	-15.24
AGE2	0.017	3.93
SEX	0.295	39.529
HIGH	-0.364	-52.387
MEDIUM	-0.546	-82.34
LOW	-0.795	-96.93
UNEMP	-0.041	-0.46
OLF	-0.084	-2.407
SELF EMP	0.118	7.494
SE	-0.266	-16.56
SEX*UNEMP	-0.066	-1.28
SEX*OLF	0.048	1.82
AGE1*UNEMP	0.054	0.55
AGE1*OLF	0.096	1.66
AGE2*UNEMP	-0.05	-1.44
AGE2*OLF	0.024	1.43
HIGH*UNEMP	-0.124	-1.62
HIGH*OLF	0.014	0.5
MEDIUM*UNEMP	-0.038	-0.52
MEDIUM*OLF	0.03	1.3
LOW*UNEMP	-0.04	-0.51
LOW*OLF	0.012	0.34
UNEMP*SELF EMP	-0.002	-0.07
OLF*SELF EMP	-0.09	-5.815
$\bar{R}^2$	0.36	

Table 2: Model does not include last wage. Sample not controlled

Variable	Estimate	T-Statistic
INTERCEPT	12.61	1010.73
AGE1	-0.32	-18.93
AGE2	-0.02	-4.46
SEX	0.294	40.97
HIGH	-0.352	-54.157
MEDIUM	-0.545	-87.29
LOW	-0.79	-98.52
UNEMP	-0.119	-0.69
OLF	-0.37	-2.14
SELF EMP	0.15	9.89
SE	-0.27	-14.6
SEX*UNEMP	-0.053	-0.62
SEX*OLF	0.058	0.65
AGE1*UNEMP	0.36	2.763
AGE1*OLF	0.42	1.97
AGE2*UNEMP	0.03	0.5
AGE2*OLF	0.07	0.83
HIGH*UNEMP	-0.35	-2.37
HIGH*OLF	0.06	0.4
MEDIUM*UNEMP	-0.16	-1.12
MEDIUM*OLF	0.103	0.68
LOW*UNEMP	-0.12	-0.82
LOW*OLF	0.37	2.14
UNEMP*SELF EMP	-0.65	-9.31
OLF*SELF EMP	-0.48	-5.54
$\bar{R}^2$	0.42	

Table 3: Model does not include last wage. Sample controlled

Variable	Estimate	T-Statistic
INTERCEPT	5.08	104.88
LOG(LAST WAGE)	0.596	161.07
AGE1	-0.152	-11.62
AGE2	-0.003	-1.03
SEX	0.158	28.25
HIGH	-0.168	-32.49
MEDIUM	-0.254	-49.21
LOW	-0.359	-53.26
UNEMP	-0.384	-20.72
OLF	-0.383	-11.94
SELF EMP	0.338	28.24
SE	-0.424	-29.51
R^2	0.65	

Table 4: Model includes last wage. Individual characteristics not crossed with UNEMP

Variable	Estimate	T-Statistic
INTERCEPT	12.55	1035.78
AGE1	-0.269	-15.65
AGE2	0.018	4.36
SEX	0.297	41.95
HIGH	-0.364	-54.35
MEDIUM	-0.544	-85.10
LOW	-0.795	-101.26
UNEMP	-0.193	-12.92
OLF	-0.032	-4.26
SELF EMP	0.11	7.05
SE	-0.266	-16.58
R^2	0.36	

Table 5: Model does not include last wage. Sample not controlled. Individual characteristics not crossed with UNEMP

Variable	**Estimate**	**T-Statistic**
INTERCEPT	12.61	1011.55
AGE1	-0.312	-18.58
AGE2	-0.019	-4.40
SEX	0.294	41.19
HIGH	-0.353	-54.32
MEDIUM	-0.544	-87.30
LOW	-0.787	-98.58
UNEMP	-0.403	-16.88
OLF	-0.322	-7.81
SELF EMP	0.142	9.26
SE	-0.28	-15.15
$\bar{R}^2$	0.41	

Table 6: Model does not include last wage. Sample controlled. Individual characteristics not crossed with UNEMP

	Model A		Model B	
Variable	**Estimate**	**T-Statistic**	**Estimate**	**T-Statistic**
INTERCEPT	5.10	105.25	12.62	1003.13
LOG(LAST WAGE)	0.595	161.23	-	-
AGE1	-0.155	-11.74	-0.32	-18.81
AGE2	-0.003	-1.08	-0.02	-4.51
SEX	0.156	27.74	0.293	40.88
HIGH	-0.167	-32.31	-0.35	-54.06
MEDIUM	-0.253	-49.05	-0.542	-86.81
LOW	-0358	-53.09	-0.784	-97.9
UNEMP	-0.30	-2.27	-0.036	-0.21
OLF	-0.278	-2.06	-0.352	-2.03
SELF EMP	0-348	29.15	0.152	9.96
SE	-0416	-28.95	-0.28	-15.17
SEX*UNEMP	0.105	1.58	-0.064	-0.745
SEX*OLF	0.193	2.81	0.06	0.67
AGE1*UNEMP	0.15	1.49	0.366	2.81
AGE1*OLF	0.213	1.27	0.423	1.97
AGE2*UNEMP	0.028	0.62	0.027	0.49
AGE2*OLF	0.029	0.41	0.063	0.69
HIGH*UNEMP	-0.188	-1.637	-0.36	-2.42
HIGH*OLF	-0.022	-0.17	0.065	0.39
MEDIUM*UNEMP	-0.048	-0.44	-0.16	-1.11
MEDIUM*OLF	-0.117	-0.99	0.096	0.63
LOW*UNEMP	-0.043	-0.38	-0.123	-0.83
LOW*OLF	0.07	0.52	0.375	2.14
UNEMP*SELF EMP	-0.727	-13.29	-0.658	-9.33
OLF*SELF EMP	-0.55	-8.19	-0.474	-5.44
LONG OLF	0.14	1.15	0.113	0.72
LONG UNEMP	0.104	1.33	0.174	1.73
STUN	-0.108	-6.21	-0.22	-9.82
STOLF	-0.019	-2.66	-0.057	-6.22
R^2	0.65		0.42	

Table 7: Duration Variables. Sample controlled

The Title

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Abstract

Replace this text with your own abstract.

	Model A		Model B	
Variable	**Estimate**	**T-Statistic**	**Estimate**	**T-Statistic**
INTERCEPT	5.08	105.1	12.61	1010.85
LOG(LAST WAGE)	0.596	161.70	-	-
AGE1	-0.156	-11.79	-0.322	-18.93
AGE2	-0.003	-1.08	-0.02	-4.46
SEX	0.156	27.76	0.294	40.97
HIGH	-0.167	-32.31	-0.352	-54.16
MEDIUM	-0.254	-49.22	-0.545	-87.30
LOW	-0.359	-53.28	-0.788	-98.52
UNEMP	-0.324	-2.44	-0.10	-0.59
OLF	-0.279	-2.08	-0.371	-2.145
SELF EMP	0.348	29.16	0.151	9.90
SE	-0.413	-28.73	-0.27	-14.62
SEX*UNEMP	0.084	1.25	-0.08	-0.94
SEX*OLF	0.192	2.8	0.058	0.65
AGE1*UNEMP	0.124	1.22	0.34	2.59
AGE1*OLF	0.21	1.26	0.424	1.96
AGE2*UNEMP	0.014	0.29	0.014	0.23
AGE2*OLF	0.04	0.57	0.075	0.82
HIGH*UNEMP	-0.264	-2.26	-0.43	-2.86
HIGH*OLF	-0.025	-0.19	0.067	0.41
MEDIUM*UNEMP	-0.13	-1.18	-0.24	-1.67
MEDIUM*OLF	-0.11	-0.94	0.103	0.68
LOW*UNEMP	-0.11	-0.96	-0.19	-1.26
LOW*OLF	0.064	0.47	0.375	2.14
UNEMP*SELF EMP	-0.70	-12.83	-0.637	-8.97
OLF*SELF EMP	-0.556	-8.22	-0.483	-5.54
ELIGIBILITY	0.16	4.14	0.156	3.15
R^2	0.65		0.42	

Table 1: Eligibility: Def. n.1. Sample controlled

	Model A		Model B	
Variable	**Estimate**	**T-Statistic**	**Estimate**	**T-Statistic**
INTERCEPT	5.08	105.1	12.61	1010.78
LOG(LAST WAGE)	0.596	161.64	-	-
AGE1	-0.156	-11.79	-0.322	-18.93
AGE2	-0.003	-1.08	-0.02	-4.46
SEX	0.156	27.76	0.294	40.97
HIGH	-0.167	-32.31	-0.352	-54.16
MEDIUM	-0.254	-49.22	-0.545	-87.30
LOW	-0.359	-53.28	-0.788	-98.52
UNEMP	-0.34	-2.57	-0.11	-0.66
OLF	-0.279	-2.08	-0.371	-2.145
SELF EMP	0.348	29.14	0.151	9.90
SE	-0.413	-28.73	-0.27	-14.60
SEX*UNEMP	0.12	1.75	-0.039	-0.46
SEX*OLF	0.192	2.8	0.058	0.65
AGE1*UNEMP	0.135	1.33	0.32	2.48
AGE1*OLF	0.21	1.26	0.424	1.96
AGE2*UNEMP	0.029	0.63	0.026	0.43
AGE2*OLF	0.04	0.57	0.075	0.82
HIGH*UNEMP	-0.175	-1.52	-0.32	-2.17
HIGH*OLF	-0.025	-0.19	0.067	0.41
MEDIUM*UNEMP	-0.04	-0.36	-0.13	-0.93
MEDIUM*OLF	-0.11	-0.94	0.103	0.68
LOW*UNEMP	-0.038	-0.33	-0.11	-0.72
LOW*OLF	0.064	0.47	0.375	2.14
UNEMP*SELF EMP	-0.72	-13.83	-0.66	-9.33
OLF*SELF EMP	-0.556	-8.22	-0.483	-5.54
ELIGIBILITY	-0.035	-0.88	0.11	-2.21
R^2	0.65		0.42	

Table 2: Eligibility: Def. n.2. Sample controlled

Variable	Estimate	T-Statistic
INTERCEPT	5.03	103.86
LOG(LAST WAGE)	0.60	162.52
AGE1	-0.155	-11.72
AGE2	-0.003	-1.04
SEX	0.155	27.64
HIGH	-0.165	-32.11
MEDIUM	-0.251	-48.87
LOW	-0.356	-52.87
UNEMP	20.487	6.61
OLF	-0.282	-2.10
SELF EMP	0.348	29.22
SE	-0.412	-28.74
SEX*UNEMP	0.11	1.65
SEX*OLF	0.194	2.83
AGE1*UNEMP	0.09	0.89
AGE1*OLF	0.214	1.286
AGE2*UNEMP	-0.024	-0.52
AGE2*OLF	0.039	0.56
HIGH*UNEMP	-0.319	-2.73
HIGH*OLF	-0.02	-016
MEDIUM*UNEMP	-0.213	-1.88
MEDIUM*OLF	-011	-0.93
LOW*UNEMP	-0.323	-2.72
LOW*OLF	0.064	0.48
UNEMP*SELF EMP	-0.754	-13.75
OLF*SELF EMP	-0.558	-8.27
LOG(LAST WAGE)*UNEMP	-2.937	-5.81
$(\text{LOG(LAST WAGE)*UNEMP})^2$	0.103	5.015
R^2	0.65	

Table 3: Log(Last Wage) Polynomial. Sample controlled

	Model A		Model B	
Variable	**Estimate**	**T-Statistic**	**Estimate**	**T-Statistic**
INTERCEPT	4.48	96.3	12.36	989.7
LOG(LAST WAGE)	0.63	175.8	-	-
AGE1	-0.16	-11.9	-0.35	-19.68
AGE2	-0.001	-0.25	-0.009	-2.04
SEX	0.143	25.05	0.28	37.86
LOW	-0.147	-42.47	-0.35	-80.05
UNEMP	-0.57	-6.9	-0.56	-5.1
OLF	-0.30	-3.43	-0.346	-2.89
SELF EMP	0.37	30.57	0.17	10.72
SE	-0.435	-29.8	-0.29	-15.24
SEX*UNEMP	0.14	2.1	-0.015	-0.17
SEX*OLF	0.22	3.25	0.09	0.98
AGE1*UNEMP	0.14	1.38	0.38	2.78
AGE1*OLF	0.16	0.99	0.39	1.76
AGE2*UNEMP	0.056	1.22	0.08	1.36
AGE2*OLF	0.03	0.47	0.075	0.81
LOW*UNEMP	0.126	2.67	-0.19	-3.07
LOW*OLF	-0.063	-0.83	0.116	1.2
UNEMP*SELF EMP	-0.73	-13.22	-0.67	-8.9
OLF*SELF EMP	-0.556	-8.08	-0.47	-5.19
R^2	0.63		0.35	

Table 4: Two Educational Categories. Sample controlled