Expectations and Savings Behavior

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In partial fulfilment of the requirements for the degree of Master of Arts

Budapest, 2008

Abstract

This study shows that the expectation about future labor market status has a significant effect on the savings behavior of individuals. In the first part of the study, a simple consumption model is built. It predicts that those whose labor market status is expected to be less stable, save more/consume less to prepare for later periods of unemployment. Using data from the Health and Retirement Study, I test whether subjective job loss probability has a significant positive, and subjective job finding probability has a significant negative effect on the savings rate. Of these two, the role of uncertainty about finding a new job is found to be stronger. I show that it has a negative effect on different types of savings; the effect is robust to the use of several control variables, and also to fixed unobserved heterogeneity in the savings rate. However, the effect of the job loss probability is less clear. In the second part of this study I test whether job-loss expectations based on subjective probability questions contain hidden, otherwise unobservable information about the displacement-risk individuals face. I also develop an estimator that enables me to derive expected employment spells, and I find interesting differences between the expected and realized survival paths.

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1 Introduction

Many economic models are based on forward-looking economic agents. Their observed choices could be represeted by many alternative preference sets and expectations, so it is the researcher's task to make assumtions about their particular form. The rational expectation approach is a good candidate, because it usually yields a simple estimated relationship, and because it fits in with traditional economic thinking. Expectations are not observable characteristics of individuals, thus their form cannot be tested directly. Instead, economists frequently test the implications of the original, underlying models. These tests sometimes point at systematic empirical deviations from these predictions, which are called *puzzles*.

There are several well-known puzzles in the consumption (savings) literature as well. See e.g. Zeldes (1989), Campbell and Mankiw (1989) or Deaton (1992). Perhaps the two most well known ones are the *excess sensitivity*, and the *excess smoothness puzzles*: Consumption is correlated with anticipated changes in income, and it is less volatile than it ought to be. Several suggestions have been proposed in the literature to explain these findings. Some recommend the use of alternative utility functions, involving habit fomation, time inconsistency, etc. Others highlight the importance of different constraints, such as liquidity constraints (Zeldes, 1989) or information processing constraints (Sims, 2003). Beyond them, in the past 15 years a lot of effort has been made to understand expectation formation, and its link to economic behavior in a more fundamental way.

My paper contributes to this literature by stating that subjective data on expectations contains unique information about individuals' beliefs, and they may help improve our economic models. These questions are asked in survey situations, where interviewees have to determine the probabilities of different events. The probabilty of living up to 80 years, or the probability of losing the job within one year, etc. are such questions. Yet, many economists are sceptical about using subjective probability questions based on surveys. They say applied economics should be based on people's *observed choices*, and survey questions on expectations are suspect.

However, there is more and more evidence in modern economic literature that these subjective expectation questions are useful. There are several studies that showed that subjective expecations are good predictors of future outcomes, and the relations remain significant even after controlling for many other variables available to the econometrician. Dominitz (1998) examined the relationship between subjective income expectations and realized income; Hurd and McGarry (1997), Perozek (2005) analyzed survival expectations and mortality; Stephens (2003) explored job loss expectations and realizations. These studies found both systematic variation in expectations, and systematic departures from realizations. It means that some have more, others have less precise expectations. This latter observation is fundamental, because it can have serious consequences for the dynamic economic behavior of individuals. And of course, this is where the greatest research potential lies. Does the use of subjective expectations alter the implications of our economic models? Do subjective expectations help explain some empirical puzzles?

There is a limited number of studies where subjective expectations were included in models other than the outcomes of the expectations questions themshelves. Kézdi and Willis (2008) and Kimball et al. (2007) link subjective expectations to savings behavior and risk tolerance of households in a promising way; Japelli and Pistaferri (1998) test the excess sensitivity puzzle using subjective expectations on income; Haider and Stephens (2004) use retirement expectations to analyze the consumption of the old. Beyond the interesting qualitative inferences of these papers, it is also discernible that there is no clarified method for how the subjective probability questions should be modeled and used.

In the first part of the study I will relate labor market status expectations (both displacement and job-finding probabilities) to the savings behavior of individuals. According to most economic models, individuals do take the future into account when they make savings/consumption decisions, and they do smooth consumption according to their expectations about future income. Therefore, it is upperly interesting to test these implications using the subjective expectations about the future labor market status of people. I find that job-finding chances affect the savings rate in a significantly negative way. This finding is consistent with the theory, since lower job finding probability lead to longer expected unemployment spells, and thus lead to a lower expected present value of lifetime income. This effect is true for different types of savings; robust to the use of several control variables, and also to fixed unobserved heterogeneity in the savings rate. The effect of job-loss probabilities, however is less clear. I find that displacement is associated with lower levels of savings, but expectations about displacement play no role. The only exception is the debt rate: those who face higher displacement risk, tend to pay back some of their debts.

In the second part of this study I will show that job-loss expectations based on subjective probability questions contain unique information about the displacement-risk individuals face. I also develop an estimator that enables me to derive *expected employment spells* in a similar way as in the survival literature. I find strong time-dependence of the subjective expecations and I also find interesting deviations of expectations from realizations. The strong time-dependence of expecations means that even the parameters of the distribution (mean and variance) change with time on the individual level. These findings are supported by the learning theory. People are uncertain about their survival chances when they start their employment spells. Then, observing their success in being able to keep the job, they both become more optimistic and less uncertain.

Section 2 briefly describes the HRS study and the data problems I needed to handle. In Section 3 I derive a simple consumption model, and present the outputs of the savings regressions. In Sections 4 I present my estimator for the expected employment spells, and the outputs of the models that measure the relationship between job-loss expectations and realizations. Section 5 concludes.

2 Data

2.1 The variables used and the sample

Throughout the study I will use data from the Health and Retirement Study (HRS)[1]. HRS is a panel database, initiated in 1992. Roughly 7700 American families are interviewed biennialy, if at least one family member is old (was 50-60 years old in 1992). I use the first 8 waves of the study from 1992 to 2006.

A big advantage of the study is the part on expectations, where several probability questions are asked. The two questions I will use (p_{loss} and p_{find}) are the following:

"Sometimes people are permanently laid off from jobs that they want to keep. On the same scale from 0 to 100 where 0 equals absolutely no chance and 100 equals absolutely certain, how likely is it that you will lose your job during the next year?"

"What do you think are the chances that you could find an equally good job in the same line of work within the next few months?"

If we want to relate expectations to consumption/savings behavior, we need to have good proxies for them. However, it is difficult to capture both consumption and savings of households. In the HRS there is a limited number of questions directly about consumption or savings, but there is quite detailed information about the wealth of households. As a consequence, I have chosen to model the changes in different types of household wealth between two consecutive waves of the study.

Wealth change is, of course, strongly related to savings, but there is also an important difference. Wealth change depends not only on savings but on the actual rate of return on assets, too. Morever, there can be systematic variability in the realized rate of return among households. I cannot adjust for this factor, but hopefully this variation is much smaller than the variation in savings, and thus the effect of this measurement error is small.

[1] http://hrsonline.isr.umich.edu/

The used wealth-change variables are related to households, while most of the other variables are characteristics of individuals. Thus I restricted the sample to one family member, to the financial responder of the household. In the HRS study, only workers answered the probability questions, so throughout the analysis only they form the sample. To be more precise, only those are included who were workers in the first of two consecutive waves. These restrictions left me a sample of roughly 25,500 observations in the pooled database.

The HRS contains data on the inter-wave job-market histroy of people. Out of the 22,441 observations that appear in two consecutive waves (all observations except for the first wave) 6464 reported that their employment spell ended between the two waves. From among them 4,969 left their job voluntarily and 1,495 were either laid off, or their working-place closed. Throughout the study, these 1,495 observations will form the displaced category.

2.2 Evidence of noise

One unfavorable feature of survey data is noisiness. Moreover, answering probability questions is cognitively demanding, and we may think these variables contain significant measurement error. Figure 1-3 supports this reasoning. First, the histogram of the probability questions is not continuous, because people tend to give rounded answers. Second, the number of the so-called *focal answers*[2] (0, 50 and 100 percent) is even higher. One potential explanation for the high ratio of focal answers is that these people are really uncertain about these probabilities. My model, however, assumes certainty equivalence, so the role of uncertainty is neglected by assumption. (See Section 3)

An even more important problem is the noisiness of the financial wealth variables. Out of the available 22092 total wealth changes in the sample, at least one component of the total wealth was missing for 5631 observations, and was replaced by imputation by the HRS staff. Unfortunately, the imputation was based on cross-sectional methods[3], thus they are not reliable to model changes of financial wealth between waves. As a consequence, I

[2] See e.g. Hill et. al. (2004).
[3] See the RAND HRS documentation (version G), pp. 26 for details.

had to drop all the imputed wealth values.

Moreover, even after dropping the imputed values, there are still extreme outliers in the sample, which strongly affect the OLS estimates. As Figure 4 shows, even when I restrict the sample to those, whose wealth is less then 2m$, the joint distribution of household financial wealth at t and $t+1$ is not around the 45 degree line as expected. It indicates that this particular wealth change variable contains a lot of noise. The situation is very similar with the other wealth variables, too. This noise is probably not classical measurement error (the rich are affected more), therefore it can bias my results.

One would think that these outliers can be detected and should simply be taken out of the sample. Unfortunately I could not find a robust outlier detecting method. Instead, I chose to run probability models, which were much more robust. I defined several "positive wealth change" dummies, and I modeled saving-propensities.

3 Expectations and Savings Behavior

The purpose of this section is to test whether the expectations about future labor market status (displacement and job-finding expectations) have significant effect on the savings behavior of individuals. My research is in the spirit of Stephens (2003), who analyzed job loss expectations and their link to consumption behavior. He found strong relationship between job loss expectations and realizations, but found no evidence that these expectations affect consumption in any way. His study, however, is subject of debate. The main problem is the use of food consumption as a proxy for overall household consumption. Even if we believe that job loss expectation is linked to consumption behavior, food consumption is probably the most stable part of it[4]. In contrast, I use the change in financial wealth as a proxy for savings to examine the role of expectations in making savings and consumption decisions. My results are comperable with those of Stephens (2003), because I use the same HRS database, but with a slightly longer time-horizon.

3.1 The model

My model is a version of the widely used *consumption under uncertainty model* introduced by Flavin (1981).

3.1.1 Assumptions and notations

1. Individuals maximize the present value of their expected utility over an infinite horizon.

2. The instantaneous utility function $u(\cdot)$ is quadratic, thus we have certainty equivalence.

3. Individuals can save and borrow with the same interest rate. The expected rate of return equals to the discount rate, and is uncorrelated with everything: $E_t(r_{t+i}) = r = \delta$. However, the posterior rate of return can differ from this.

[4]However, his argument is strenghtened by the fact that displacement is associated with strictly lower levels of consumption too.

4. Individuals lose their job during one period with probability p_l, and find a job with probability p_f.

5. If an individual is working, he receives labor income w. When he is unemployed, he receives unemployment benefit $u < w$.

3.1.2 The problem and the optimum

The problem of an individual:

$$\begin{aligned} &\max_{c_{t+i}} \sum_{i=0}^{\infty} \frac{E_{t+i}(u(C_{t+i}))}{(1+\delta)^i} \\ s.t. \quad : \quad &\sum_{i=0}^{\infty} \frac{E_{t+i}(C_{t+i})}{(1+r)^i} \leq A_t + \sum_{i=0}^{\infty} \frac{E_{t+i}(Y_{t+i})}{(1+r)^i} \end{aligned}$$

The Euler equation is:

$$u'(C_t) = \frac{1+\delta}{1+r} E_t(u'(C_{t+1}))$$

Using that the interest rate equals to the discount rate and that the instantaneous utility function is quadratic:

$$C_t = E_t(C_{t+1}) \tag{1}$$

Using the budget constraint gives the well-known formula:

$$\begin{aligned} C_t &= \frac{r}{1+r}\left[A_t + H_t\right] \qquad (2) \\ H_t &\equiv \sum_{i=0}^{\infty} \frac{E_{t+i}(Y_{t+i})}{(1+r)^i}, \end{aligned}$$

where H_t is the present value of expected lifetime income. Using that one-period income can only take two values (w and u), we can express H_t^w and H_t^u, the present value of lifetime income if the worker is employed or not:

$$\begin{aligned} H_t^w &= w + \frac{1}{1+r}\left[p_l H_t^u + (1-p_l) H_t^w\right] \\ H_t^u &= u + \frac{1}{1+r}\left[p_f H_t^w + (1-p_f) H_t^u\right] \end{aligned}$$

The solution is:

$$\begin{aligned} H_t^w &= \frac{1+r}{r}\left(\frac{w(r+p_f)+up_l}{p_f+p_l+r}\right) \\ H_t^w &= \frac{1+r}{r}\left(\frac{wp_f+u(r+p_l)}{p_f+p_l+r}\right) \end{aligned}$$

Plugging this back into (2) yields:

$$\begin{aligned} C_t^w &= \frac{r}{1+r}(A_t + H_t^w) = \frac{rA_t}{1+r} + \frac{w(p_f+r)+up_l}{(p_f+p_l+r)} \qquad (3) \\ C_t^u &= \frac{r}{1+r}(A_t + H_t^u) = \frac{rA_t}{1+r} + \frac{wp_f+u\,(r+p_l)}{(p_f+p_l+r)} \end{aligned}$$

Note that the consumption differs in the working and in the non-working periods.

3.1.3 Optimal wealth expansion

In the HRS database we do not have realistic proxies for consumption, but we have detailed information on the wealth of households. In our model wealth is given by:

$$A_{t+1} = (1 + r_t)(A_t + Y_t - C_t) = (1 + r_t)(A_t + S_t) \tag{4}$$

Note that in (4) we use posterior rate of return r_t instead of expected rate of return r. Using the optimal consumption path (3) we can derive the optimal savings path:

$$\begin{aligned} S^w &= w - C^w = -\frac{rA_t}{1+r} + p_l \frac{w-u}{r+p_f+p_l} \\ S^u &= u - C^w = -\frac{rA_t}{1+r} - p_f \frac{w-u}{r+p_f+p_l} \end{aligned}$$

Plugging them back to (4):

$$\begin{aligned} \Delta A^w_{t+1} &= r_t A_t + (1+r_t)S^w = \frac{r_t - r}{1+r} A_t + \frac{(1+r_t)p_l(w-u)}{r+p_f+p_l} \\ \Delta A^u_{t+1} &= r_t A_t + (1+r_t)S^u = \frac{r_t - r}{1+r} A_t - \frac{(1+r_t)p_f(w-u)}{r+p_f+p_l} \end{aligned}$$

Here ΔA^w_{t+1} means the change in wealth between t and $t+1$ if the individual worked at t. Note that if posterior rate of return is lower than its expected value, the change in wealth can be easily negative even in a working period.

Let us derive the derivatives of wealth change with respect to the exogenous parameters. Let us start with the probabilities:

$$
\begin{aligned}
\frac{\partial(A^w_{t+1})}{\partial p_l} &= \frac{(1+r_t)(r+p_f)(w-u)}{(r+p_f+p_l)^2} \\
\frac{\partial(A^u_{t+1})}{\partial p_l} &= \frac{p_f(1+r_t)(w-u)}{(r+p_f+p_l)^2} \\
\frac{\partial(A^w_{t+1})}{\partial p_f} &= -\frac{p_l(1+r_t)(w-u)}{(r+p_f+p_l)^2} \\
\frac{\partial(A^u_{t+1})}{\partial p_f} &= -\frac{(r+p_l)(1+r_t)(w-u)}{(r+p_f+p_l)^2}
\end{aligned}
$$

Taking the natural restrictions on these parameters into account we can order the derivatives in the following way:

$$
\frac{\partial(A^u_{t+1})}{\partial p_f} < \frac{\partial(A^w_{t+1})}{\partial p_f} < 0 < \frac{\partial(A^u_{t+1})}{\partial p_l} < \frac{\partial(A^w_{t+1})}{\partial p_l}
$$

That is, the higher the job loss probability, the greater the wealth-expansion. This is because individuals at risk of job loss have to prepare more for later unemployed periods. Conversely, the higher the job finding probability, the lower the wealth expansion, because if it is easier to find a job, the unemployed periods are less harmful. We can also see that job loss probability is supposed to have higher effect on workers, while job finding probability should effect the unemployed more.

Let us now compute the derivatives of A^w_{t+1} with respect to the income variables:

$$\frac{\partial(WE^{w}_{t+1})}{\partial w} = \frac{p_l(1+r_t)}{r+p_f+p_l}$$
$$\frac{\partial(WE^{u}_{t+1})}{\partial w} = -\frac{p_f(1+r_t)}{r+p_f+p_l}$$
$$\frac{\partial(WE^{w}_{t+1})}{\partial u} = -\frac{p_l(1+r_t)}{r+p_f+p_l}$$
$$\frac{\partial(WE^{u}_{t+1})}{\partial u} = \frac{p_f(1+r_t)}{r+p_f+p_l}$$

The ordering of these effects is less clear, because it depends on the ordering of the probabilities. However, we can see that the absolute values of the effects of labor income and unemployment benefit are the same.

3.1.4 Positive wealth expansion

In the empirical part of my study I will estimate probability models, where the probability of a positive wealth expansion will be on the left hand side. In my model the optimal wealth change in a working period is positive if:

$$\Delta A^{w}_{t+1} = \frac{r_t - r}{1+r}A_t + \frac{(1+r_t)p_l(w-u)}{r+p_f+p_l} > 0 \tag{5}$$
$$\frac{p_l}{r+p_f+p_l} > \frac{(r-r_t)}{(1+r)(1+r_t)}\frac{A_t}{(w-u)}$$

The left hand side of this inequality is surely positive, while the right hand side can be both positive and negative.

The optimal wealth change in an unemployed period is positive if:

$$
\begin{aligned}
\Delta A^{u}_{t+1} &= \frac{r_t - r}{1+r} A_t - \frac{(1+r_t) p_f (w-u)}{r + p_f + p_l} > 0 \\
-\frac{p_f}{r + p_f + p_l} &> \frac{(r - r_t)}{(1+r)(1+r_t)} \frac{A_t}{(w-u)}
\end{aligned}
$$

Now the left hand side of this inequality is surely negative, while the right hand side can be both positive and negative. Note that if the posterior rate of return equals to its expected value ($r_t = r$), people always save in a working period, and always dissave in an unemployed period. The derivatives of the left hand sides are positive with respect to p_l, and negative with respect to p_f. So the higher the job-loss probability, the more likely that an individual will save, and conversely, the higher the job-finding probability, the more likely that she will dissave. These are the predections of the model, I would like to test.

3.1.5 Implications and limitations of the model

The model has two important predictions:

1. Consumption and savings can differ in periods of employment and unemployment.
2. Consumption and savings are affected by expectations about future labor market status. Those who expect a higher probability of job loss or a lower probability of finding a job, consume less and save more.

These predictions are in line with the original model of Flavin (1981). Higher job loss probability and lower job finding probability lead to shorter expected employment and longer expected unemployment spells, and thus lead to a lower expected present value of lifetime income. A rational agent should take it into account when she makes consumption decision: she should save more/consume less to prepare for later periods of unemployment.

The used model is the simplest possible to derive a link between job loss expectations and consumption, and has at least two important deficiencies:

1. Role of uncertainty: In my model a quadratic utility function is assumed that implies certainty equivalence. It means that only the mean of the probability-distribution affects consumption, while the variance (uncertainty) is not important. However, uncertainty may play an important role in economic decision making. For simplicity, this factor is disregarded in my analysis.

2. Myopic behavior: In my model standard exponential discounting is assumed. Discount factors other than exponential (e.g. hyperbolic) enable myopic behavior, that is, time-inconsistency can arise. The purpose of my study is to show that expectations about future do affect present consumption. Whether expectations are rational (time-consistent), or not is out of the scope of this paper.

3.2 Identification method

As I said before, I will estimate probability models for savings. The simplest possible econometric model for testing my original hypothesis is the following:

$$I(\Delta A_{t+1} > 0) = \alpha_0 + \alpha_1 p_{lt} + \alpha_2 p_{ft} + \underline{\beta}' \cdot \underline{controls}_t + \varepsilon_t, \tag{6}$$

where $I()$ is an indicator function of positive savings. According to my model, in any specification I expect α_1 to be positive and α_2 to be negative.

3.2.1 The left hand side

There is detailed information in the HRS about the assets and wealth of households in every wave of the study. I will use seven different wealth variables: three aggregated and four detailed ones. By estimating more models, I can both check the robustness of my results, and potentially capture more complex asset reallocation. It is possible, for example, that the expectations only affect the short-term savings, and not the long-term ones. It is also possible that the expectations have a different effect on the savings and on the debts of households, etc.

The wealth variables used will be the following:

1. non-retirement household savings (S1): Money kept in stocks, bonds, checkings, or any other types of savings.
2. net value of household debts (S2): Mortgage loans, other housing debts and any other types of household debts. Net value means that this variable is negative, beacuse it indicates negative wealth.
3. household retirement savings (S3): Money in the family members' Individual Retirement Accounts (IRA).
4. fixed assets of households(S4): Vehicles, real estates and business ownerships.
5. Overall non-retirement financial wealth (S5): The sum of S1 and S2.
6. Overall financial wealth (S6): The sum of S1, S2 and S3.
7. Overall household wealth (S7): The sum of S1, S2, S3 and S4.

According to Table 1, the variation in all these wealth variables is high. Approximately half of the observations exhibited positive and half of them exhibited negative wealth change. This is good for us, because it makes the identification of the coefficients of interest easier. We can also see, that the number of wealth-change observations is quite different. The reason for this, as I mentioned above, is the large number of missing values.

3.2.2 Control variables

In order to get unbiased estimates of the parameters I have to use several types of controls variables:

1. *Variables from my model:* According to (5) a worker saves if $\frac{p_l}{r+p_f+p_l} > \frac{(r-r_t)}{(1+r)(1+r_t)} \frac{A_t}{(w-u)}$. This suggests including earnings and wealth variables into the model. I will use all the detailed wealth variables (S1-S4).

2. *Human capital variables:* I include education and age dummies, because they may correlate with both the permanent income and the expectations.

3. *Labor market variables:* I include occupation dummies, and a variable that indicates whether the individual has a second job or not.

4. *Future labor market status:* According to (6) I regress wealth changes between time t and $t+1$ on time t characteristics. The timing of the model however can be different in reality, because job-loss is not a discrete process. People can lose their job at any time between two consecutive waves, which would alter their savings behavior. However, if I control for later displacement and job-leaving (between time t and $t+1$), I can separate their effect from the effect of prior expecations about displacement (at time t). Of course, with this functional form the effect of expectations is assumed to be the same among the later displaced and among those who can keep their original jobs. Fortunately, the estimations are not sensitive to this restriction.

5. *Technical variables:* I include time dummies to allow for fixed time effects.

6. Other variables: I include marital status, gender, race and residence dummies.

3.2.3 Choice of econometric model

My basic regressions will be estimated by pooled OLS, with different sets of control variables. Beyond the OLS I will also estimate probit, fixed effect and IV models. The fixed effect models identify from changes in the variables. Thus, at the cost of higher standard errors, they are also robust to fixed unobserved heterogeneity in savings.

As we can see on the histogram of the probability questions, people tended to give rounded answers. It means that these variables contain notable measurement error. Because they appear on the right hand side of the equations, we expect a downward bias (in absolute value) of the coefficients. In order to get rid of this bias, I estimate IV models, too. In these models I instrument both probability variables (displacement and job-finding) with tenure and industry dummies. These variables are strongly correlated to both displacement and expectations, but they probably do not have an effect on conditional savings. I did not find evidence or any serious argument for why the saving propensity should differ in different industries for reasons other than the difference in average earnings and in the average job reallocations rate.[5]

3.3 Results

The outputs of the regressions can be found in the Appendix. Tables 2-4 contain the models for the aggregated wealth-change variables, and Tables 5-8 for the detailed ones. Overall, the effect of the job finding probability is found to be negative in nearly all of the specifications. The estimated coefficients are between negative 2-5 percent in the OLS, probit and FE cases, and notably smaller (higher in absolute value) in the IV models. A negative 5 percent effect means that those who are absolutely sure about their success in finding a job quickly in case of job-loss ($p_f = 1$), are 5 percent less likely to save than those who think this probability is zero. This effect may seem small, but when we compare it to the coefficients of displacement (∼negative 2-6 percent), we find that these effects have approximately the same order of magnitude.

Except for the IV specifications, the estimated effects of job-finding expectations are quite similar in all specifications, and for all wealth categories. In the OLS and probit models the effects are usually significant at 5 percent, but they sometimes lose their significance in the fixed-effect models. This is not surprising, because the standard errors of the FE estimator are usually higher than the ones of the OLS models.

Perhaps the most surprising results come from the IV models. The reason for instrumenting the probability variables was to handle the strong measurement error due to rounding. The IV models give very similar, but not significant coefficients, when the non-retirement savings or the household debts appear on the left-hand side (Tables 5-6). However, the estimated effects are negative 24 percent (!) for the retirement savings and negative 20 percent for the fixed assets. These effects are very high. It seems that the differences in expectations by sectors and tenure play a really important role in long-term savings

[5] The only argument that questions the validity of my instruments is the sectoral differences in the use and extent of retirement plans, which possibly correlate with savings.

decisions.

However, the effect of job loss expectations is less clear. In the majority of the specifications the estimated coefficients are fluctuating around zero, and they are not significant. One exception is the debt rate: according to the OLS and probit models, people at risk of job loss are significantly more likely to pay back some of their debts. The other interesting result comes from the models for the retirement savings. Here the IV models show a qualitatively different result than the other estimators: the estimated effect is postive 40 percent (!). The estimations, thus, are really sensitive to the econometric specification. Further investigations should be made to understand this phenomenon.

Overall, the effect of the job finding probability is found to be negative and robust, while the effect of the job-loss probability fluctuates around zero and is sensitive to specification. At the first sight, it seems strange that the job-finding probability has the stronger effect on the savings. The probability of displacement affects the expected income even in the short run, while the probability of finding a job (of a worker) affects it only in the medium or long-run.

Investigating the histogram of the job-loss probability gives one potential explanation for this finding. Zero probability is assigned to more than half of the sample. Displacement is a rare event, and it is reasonable to think that people can estimate the probabilities of rare events more poorly. It is also possible, that the savings behavior of the zero responder majority and the non-zero responder minority is completely different. It is possible, for example, that only the non-zero responders are myopic, who do not take expected future income into account when they make consumption/savings decisions.

4 Job loss expecations and realization

In this Section I will investigate the job loss expectations in a more structural way. In the first part of the Section I compare expectations and realized displacement with descriptive statistics and regressions. Then I will develop a maximum likelihood estimator that enables me to derive expected employment spells.

4.1 Descriptive analysis

Table 9 shows the average displacement rate and the average of the subjective job-loss probabilities broken down by some important demographic and labor market related variables. Table 10 shows the major determinants of job loss expectations and displacement. First, we can see that the average displacement rate is less than half of the average probability people assign to displacement. Moreover, displacement is measured between two consecutive waves of the HRS, so it corresponds to the number of displaced workers within two year-periods. It indicates that, on average, people are strongly pessimistic about their job-keeping chances.

However, we can also see that the same variables correlate with both the expectations and the realized displacement. The major determinant in both cases is tenure, which has a strong negative effect on both expectations and displacement. Second, perhaps more surprisingly, there is more observed variability in expectations than in displacement: age, race and earnings seem to have stronger effect on expectations than on realized displacement. One explanation for this phenomenon is that these variables are important predictors of *expectation error*.

The probability questions contain notable measurement error. However, Table 11 shows that job loss probability is strongly related to displacement, as it is significant at any significance level. The estimated parameters in the different specifications are between 0.128 and 0.152. What is really important to us is that the coefficients of expectations remain strongly significant even when I control for a large set of variables. It means, that these probability questions contain unique, otherwise unavailable information about the displacement risk individuals face.

Figures 1-2 show the distribution of the job loss probabilities by future displacement status of individuals. We can see that even if the average job loss expectation among those later displaced is higher, still the majority expected 0 probability for displacement. The ratio of 0 answers, however, are much lower than among those who could keep their jobs (36 percent compared to 54 percent).

Overall, I found that these probability questions contain really important and unique information about the risk of displacement. However, the way people answer these questions, and the way they make errors is less trivial. Therefore, to be able to investigate job-loss expectations in a more fundamental way, I have to go deeper into the understanding of expectation formation.

4.2 Expected and realized employment spells

In this Subsection I develop a maximum likelihood based estimator, with which I can derive expected survival paths of people. Survival, throughout this section, refers to the chance that somebody can keep her job until a specific time. The survival function is a $S(X_i, t) \longrightarrow (0, 1)$ function that gives us the probability that somebody with characteristics X_i keeps her job until t years after the start of the employment spell.

My purpose is to derive expected survival paths and to relate them to the empirical survival functions. When I estimate empirical survival functions, the probabilities are approximated by the number of non-displaced workers until t over the number of workers[6]. Note that when I estimate expected survival paths, I have much more information about the form of this function, because I have information about the probabilities for *everybody*. This observation is fundamental, because it enables me to understand the structure of expectations more precisely. Particularly, I will use this extra information to derive the time-dependence of the expectations. Moreover, my estimator will tackle problems related to rounded probability answers.

[6] And of course a specific functional form is used when we estimate parametric models.

4.2.1 The empirical survival model

Let us see first the derivation of the empirical survival function. I use the log-normal density function (and log-normal hazard function) for modelling the time of displacement, because it fits the data quite well. The log-normal hazard function, with reasonable parameters, increases quickly at the beginning of a spell, and then gradually starts to decrease. This is the feature of the hazard function, which is needed to properly model the employment spells. The other adventage of the log-normal specification is that the two parameters of this distribution, the mean and the variance of the log-spell, have easily interpretable economic meanings.

Thus the underlying model:

$$\begin{aligned} \ln(T^d) &= X_d\beta_d + u \\ u &\sim N(0, \sigma_d^2), \end{aligned} \tag{7}$$

where T^d is the time until displacement, or in other words the length of the employment spell, if the spell ended with displacement. The likelihood of one such employment spell is:

$$l_i^{emp} = \frac{\phi\left(\frac{\ln(T_i^d) - X_{di}\beta_d}{\sigma_d}\right)}{\sigma_d}$$

Note, that in the survival literature the likelihood function is usually a bit different,[7] because they write out the probability distribution as a function of T instead of $ln(T)$. The maximum points of these functions, of course, are at the same place.

Now we know the likelihood of a terminated employment spell. For a large fraction of the sample, however, we cannot observe the time until displacement for two reasons:

[7] $l_i^{emp} = \frac{\phi\left(\frac{\ln(T_i^d) - X_{di}\beta_d}{\sigma_d}\right)}{\sigma_d T_i^d}$

1. Some people can keep their original jobs until the end of the sampling period

2. Some people leave their jobs voluntarily

In the Survival literature these problems are called data censoring: the length of the spells are not observed for everybody. For them, we only know that the spell-length is at least the minimum of the sample time and the time of job-leaving. Let us denote the the minimum of the sampling time and job-leaving time with $T^{cd} \equiv \min(T^{sampling}, T^{job-leaving})$. Then the overall likelihood can be expressed as:

$$l_i^{emp} = \begin{cases} \frac{\phi\left(\frac{\ln(T_i^d)-X_{di}\beta_d}{\sigma_d}\right)}{\sigma_d} & \text{if } i \text{ is } \textit{displaced} \\ 1-\Phi\left(\frac{\ln(T_i^{cd})-X_{di}\beta_d}{\sigma_d}\right) & \text{if } i \text{ is not } \textit{displaced} \end{cases} \tag{8}$$

When a spell can end for two or more reasons, we can estimate competing risk models. In our case, an employment spell can end because of displacement or voluntary separation. If we assume that these events are independent, we can simply estimate the two models separately: one for displacement, and one for job-leaving. The first will be the same as given in (8), and the second will be:

$$l_i^{leave} = \begin{cases} \frac{\phi\left(\frac{\ln(T_i^l)-X_{li}\beta_l}{\sigma_l}\right)}{\sigma_l} & \text{if } i \text{ leaves her job} \\ 1-\Phi\left(\frac{\ln(T_i^{cl})-X_{li}\beta_l}{\sigma_l}\right) & \text{if } i \text{ does not leave her job} \end{cases}$$

where T^l denotes time until job-leaving and $T^{cl} \equiv \min(T^{sampling}, T^d)$.

A generalization of this model is when we also model uncertainty. According to (7), we can use conditional heteroskedasticity models, when we complete the models in the following way:

$$\ln(\sigma) = \beta_\sigma X_\sigma$$

We usually model the log of the standard deviation, because in such models the variance is assured to be positive.

4.2.2 The model for expectations

The underlying model is assumed to be very similar to (7):

$$\begin{aligned}
\ln(T_i^d) &= X_{ei}\beta_e + u_i \\
u_i &= u_{ci} + u_{pi} \\
\begin{pmatrix} u_{ci} \\ u_{pi} \end{pmatrix} &\sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_c^2 & 0 \\ 0 & \sigma_p^2 \end{bmatrix} \right)
\end{aligned}$$

where u_{ci} is the unobserved heterogeneity in the mean of the log-spell (known to each individual) and u_{pi} is the subjective uncertainty about the spell-length. Note that here T_i^d is not a known number (time of displacement) as in the empirical survival model. Now, given the probability answers, I will estimate the whole distribution function for everybody.

From now on, let us denote $\mu_i = X_i\beta + u_{ci}$, that is the mean of the log-spell, known to individual i. The subjective probability of survival until next year then follows a truncated log-normal distribution:

$$1 - P\left(T_i^d \leq T_i + 1 | T_i^d > T_i\right) = \frac{1 - \Phi\left(\frac{\ln(T_i+1) - X_i\beta - u_{ci}}{\sigma_p}\right)}{1 - \Phi\left(\frac{\ln(T_i) - X_i\beta - u_{ci}}{\sigma_p}\right)} = \frac{\Phi\left(\frac{\mu_i - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{\mu_i - \ln(T_i)}{\sigma_p}\right)}$$

where T_i is the length of the spell when the individual gave the probability answer. This is the job tenure.

The probability of displacement (this variable is used in the HRS):

$$P_{loss} = 1 - \frac{\Phi\left(\frac{\mu_i - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{\mu_i - \ln(T_i)}{\sigma_p}\right)} = G\left(u_{ci}, X_i\beta, T_i, \sigma_p\right)$$

Observing the probability answers, the only random variable is u_{ci}. In order to derive the likelihood function we need the take the inverse of this function with respect to u_{ci}:

$$u_{ci} = G^{-1}\left(P_{loss}, X_i\beta, T_i, \sigma_p\right)$$

Unfortunately there is no closed formula for the inverse of the truncated normal distribution. $G(\cdot)$, however, is a strictly montonically decreasing function (see Theorem 1 in the Appendix), thus the inverse exists, and we can derive it using numerical methods. This method can also be found in the Appendix. Once we have the inverse, the outcome of the random variable u_{ci} is determined. Then, the likelihood function can be expressed as:

$$l_i^e = \frac{\phi\left(\frac{G^{-1}\left(\beta, T_i^W, \sigma_p | P_{loss}, X_i\right)}{\sigma_c}\right)}{\sigma_c}$$

Rounded answers:

In the histogram of the job-loss probability answers (Table 1) we can see that a large fraction of people gave answers that were rounded to the closest multiple of 10 percent. One way to model the rounding of the probability answers is to assume that when we observe a P_{loss} answer, we only know that the true subjective probability is somewhere in the $\left(\underline{P}_{loss}, \overline{P}_{loss}\right]$ interval, where $\underline{P}_{loss}$ and $\overline{P}_{loss}$ are the closest multiples of 10 percent. Then the likelihood becomes:

$$l_i^{er} = \Phi\left(\frac{G^{-1}\left(\beta, T_i, \sigma_p | \underline{P}_{loss}, X_i\right)}{\sigma_c}\right) - \Phi\left(\frac{G^{-1}\left(\beta, T_i, \sigma_p | \overline{P}_{loss}, X_i\right)}{\sigma_c}\right)$$

Note that $G^{-1}(\cdot)$ is a monotonically decreasing function, so $\Phi\left(\underline{P}_{loss}, \cdot\right)$ appears with a positive and $\Phi\left(\overline{P}_{loss}, \cdot\right)$ with a negative sign.

4.2.3 Results

The output tables can be found in Tables 12-13 (realized survival) and Table 14 (expected survival) in the Appendix. I also created several figures to visualise these survival functions broken down by some important variables.

Before I turn to the interpretation of the results I have to emphasize an important difference between the modeling of the realized and the expected survival functions. Although the points of both survival functions are time-dependent, in the expected survival case time-dependence can be generalized. Technically it means that tenure (the current length of the spell; or time) can appear in the estimated equations of the mean and the variance of the distribution. Economically it means that I can derive different survival functions for people with different tenure. In the realized survival case, as time passes, people only move on the survival function from the left to the right. In the expected survival case, however, as time goes by, people can land on completely new survival functions. You can think of this as a learning process. People are not aware of their survival chances (technically they do not know their specific μ_i and σ_{pi}), but they learn it with time. At the beginning they have some idea, but then, observing their success in keeping their jobs, they can modify their expectations. I can do this kind of generalization of the time-dependence based on the extra information, that I observe the one-year subjective survival chances of everybody; I know much more than a binary success/failure variable.

And the main message of the outputs of these estimations is exactly the strong time-dependence of expectations. The expected mean of the log-spell (μ_i) is increasing, and the expected uncertainty about the log-spell (σ_{pi}) is decreasing with tenure. These findings are in line with the learning-approach mentioned above. People are uncertain about their survival chances when they start working at a specific place. Then, observing their success in keeping the job, their uncertainty decreases, and their optimism increases.

You can see the expected and realized survival functions broken down by tenure (time) and other important variables in Figures 7-10. You can see that at the beginning of a spell people are overly pessimistic about their survival chances, but later they become overly optimistic.[8] The time-dependence of the expected survival functions can have serious economic consequences. If people are making economic decisions based on their

[8] In models, where tenure was not included in the estimated equations, the mean survival functions resambled the ones, where tenure equals 10. This is not surprising, because the average tenure in the sample is ∼12. Those specifications, thus led to a qualitatively different result, because the subjective survival chances of people were overly optimistic rather than pessimistic at the beginning of the spell. Those specifications, however were clearly wrong, because, for example, the error-terms of the models (u_{ci}) were strongly time dependent, which makes it impossible to model properly the time-dependence of people with mean characteristincs. In the final models, the time dependence of the error terms reduced heavily, although they did not disappear completely.

subjective expectations, and their expecation error has strong time-dependence, then the economic models that incorporate only realized survival chances can be misspecified.

In the figures in the Appendix, we can also see interesting variation in expectations by gender, race and education. We can see that although the true survival chances of blacks are much better than the whites', their expectations are more pessimistic. The situation is similar with education. The expectations of the educated are poorer, while their chances are notably better. Note that this is not necessarily a contradiction, because it can also mean that the expectation error of the educated is smaller than average.

Overall, the main message of this Section was the proof of the strong time-dependence of the subjective survival expectations. Further investigations should be made to understand why this is so, and what its economic consequences are.

5 Conclusion

This study has shown that expectation about future labor market status has a significant effect on the savings behavior of individuals. According to the theory, higher job loss probability and lower job finding probability lead to lower expected present value of lifetime income. A rational agent should take this into account, and she should save more to prepare for later periods of unemployment. Using data from the Health and Retirement Study, I found that the job finding probability has a significant negative effect on the savings rate. This effect was found to be true for different types of savings; was robust to the use of several control variables, and also to fixed unobserved heterogeneity in the savings rate. The effect of job-loss probabilities however was less clear.

In the second part of the study I developed a maximum likelihood based estimator for the subjective expected survival functions. I found strong time-dependence of the subjective expecations and I also found interesting deviations of expectations from realizations. The strong time-dependence of expectations means that even the parameters of the probability distribution (the mean and the variance) change with time on the individual level. These findings are supported by learning theory. People are uncertain about their survival chances when they start their employment spells. Then, observing their success in keeping the job, their uncertainty decreases, and their optimism (regarding the expected mean of the spell) increases.

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6 Appendix

6.1 Proof of Theorem 1

The proof is based on the idea of Bagnoli and Bergstrom (2004).

Theorem 1 $G(u_{ci}, X_i\beta, T_i, \sigma_p) = 1 - \frac{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i)}{\sigma_p}\right)}$ *is a strictly monotonically decreasing function of* u_{ci}.

Lemma 2 $\frac{\phi'(x)}{\phi(x)}$ *is a monotonically decreasing function of x.*

Proof.

$$\begin{aligned}
\phi(x) &= \frac{1}{\sqrt{2\pi}}\exp(-\frac{x^2}{2}) \\
\phi'(x) &= \frac{-x}{\sqrt{2\pi}}\exp(-\frac{x^2}{2}) \\
\frac{\phi'(x)}{\phi(x)} &= \frac{\frac{-x}{\sqrt{2\pi}}\exp(-\frac{x^2}{2})}{\frac{1}{\sqrt{2\pi}}\exp(-\frac{x^2}{2})} = -x \\
\frac{\partial\frac{\phi'(x)}{\phi(x)}}{\partial x} &= -1
\end{aligned}$$

■

Lemma 3 *The inverse Mills Ratio,* $\frac{\phi(x)}{\Phi(x)}$ *is a strictly monotonically decresing function.*

Proof. We need:

$$\frac{\partial\frac{\phi(x)}{\Phi(x)}}{\partial x} < 0$$

$$\begin{aligned}
\Leftrightarrow \quad & \frac{\phi'(x)\Phi(x) - \phi^2(x)}{\Phi^2(x)} < 0 \\
\Leftrightarrow \quad & \phi'(x)\Phi(x) - \phi^2(x) < 0
\end{aligned}$$

Let us devide both sides of the inequality by $\Phi(x)\phi(x) > 0$:

$$\begin{aligned}\frac{\phi'(x)}{\phi(x)} - \frac{\phi(x)}{\Phi(x)} &< 0 \\ \frac{\phi'(x)}{\phi(x)} &< \frac{\phi(x)}{\Phi(x)} = \lim_{n \longrightarrow \infty} \frac{\phi(x) - \phi(n)}{\Phi(x) - \Phi(n)}\end{aligned}$$

According to the generalized mean value theorem (the Cauchy mean value theorem) we know $\exists \xi \in (n, x)$:

$$\lim_{n \longrightarrow \infty} \frac{\phi(x) - \phi(n)}{\Phi(x) - \Phi(n)} = \frac{\phi'(\xi)}{\phi(\xi)}$$

Because $\lim_{n \longrightarrow \infty} \phi(n) = \lim_{n \longrightarrow \infty} \Phi(n) = 0$.

Thus we need:

$$\frac{\phi'(x)}{\phi(x)} < \frac{\phi'(\xi)}{\phi(\xi)}$$

Which is true because of Lemma 2, and because $\xi < x$. ■

Proof of Theorem 1. We need:

$$\frac{\partial G\left(u_{ci}, X_i\beta, T_i, \sigma_p\right)}{\partial u_{ci}} = \frac{\partial\left[1 - \frac{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i)}{\sigma_p}\right)}\right]}{\partial u_{ci}} < 0$$

This is true if:

$$\frac{\partial\left[\frac{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i)}{\sigma_p}\right)}\right]}{\partial u_{ci}} > 0$$

The $ln()$ function is a monotonically increasing function, so the inequality holds if:

$$\frac{\partial \ln\left[\frac{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta + u_{ci} - \ln(T_i)}{\sigma_p}\right)}\right]}{\partial u_{ci}} > 0$$

$$\Leftrightarrow \quad \frac{\partial\left[\ln(\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i+1)}{\sigma_p}\right)) - \ln(\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i)}{\sigma_p}\right)\right]}{\partial u_{ci}} > 0$$

$$\Leftrightarrow \quad \frac{\phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i+1)}{\sigma_p}\right)}{\sigma_p\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i+1)}{\sigma_p}\right)} - \frac{\phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i)}{\sigma_p}\right)}{\sigma_p\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i)}{\sigma_p}\right)} > 0$$

σ_p is always positive, so I can multiply the inequality with it:

$$\Leftrightarrow \frac{\phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i+1)}{\sigma_p}\right)} - \frac{\phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i)}{\sigma_p}\right)}{\Phi\left(\frac{X_i\beta+u_{ci}-\ln(T_i)}{\sigma_p}\right)} > 0$$

And this is always true, because of Lemma 3, and because $-\ln(T_i+1)$ is smaller than $-\ln(T_i)$. ■

6.2 Numerical root-finding

The task is to find the root of $(G\,(u_{ci}, X_i\beta, T_i, \sigma_p) - P_{loss}) = 1 - \frac{\Phi\left(\frac{\mu_i-\ln(T_i+1)}{\sigma_p}\right)}{\Phi\left(\frac{\mu_i-\ln(T_i)}{\sigma_p}\right)} - P_{loss}$ with respect to u_{ci}. u_{ci} is a normally distributed random variable so $n_{ci} := \Phi(\frac{u_{ci}}{\sigma_c}) \in [0,1]$, and there is a one-to-one relationship between u_{ci} and n_{ci}. Throughout the algoritmh I will try several points in the [0,1] interval, take the inverse normal of it, and check weather the given number is the root of the given function, or not. If not, I always know in which direction to move, because the given function is monotonically decresing in u_{ci}. The steps of the algorithm:

1. I take $n^0_{ci} = 0.5$, and I check weather $(G\left(\Phi^{-1}(n^0_{ci})\sigma_c, X_i\beta, T_i, \sigma_p\right) - P_{loss})$ is positive or negative.

2. If positive, then I know that the root, in terms of n_{ci} must be in the $[0, 0.5)$ interval. If it is negative, then I know n_{ci} is in the $(0.5, 1]$ interval. In this step I halve the possibly good interval again: If the function was positive, I take $n^1_{ci} = 0.25$, if it was negative, I take $n^1_{ci} = 0.75$. Then I check again weather $(G\left(\Phi^{-1}(n^1_{ci})\sigma_c, X_i\beta, T_i, \sigma_p\right) - P_{loss})$ is positive or negative.

3. I continue these steps 50 times.

Note that in every steps I halve the possibly good interval of the root of the function. Therefore after 50 iterations, I get the root by $O(2^{-50}) = O(10^{-15})$ precision, which is enough to get a good approximation of the likelihood function.

6.3 Tables and Figures

Figure 1: **Histogram of the Job Loss Probabilites in the HRS, 1992-2006**

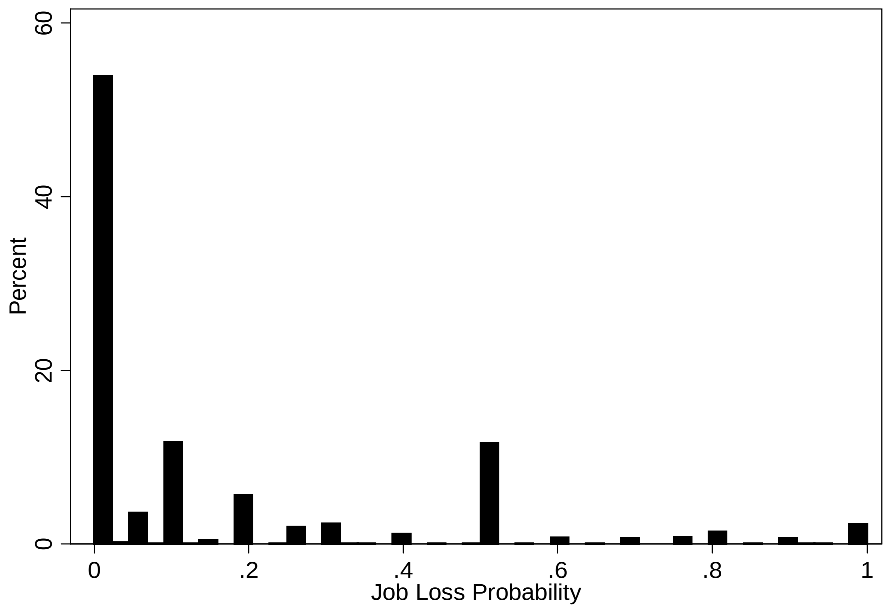

Figure 2: **Histogram of the Job Loss Probabilites among those, who will be displaced, 1992-2006**

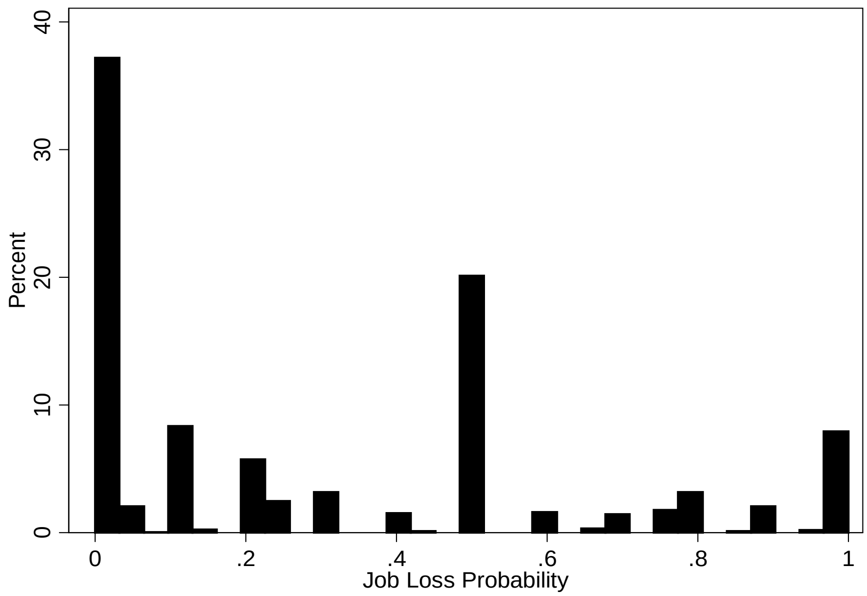

Table 1: **Number of Observations with Positive Wealth Change**

	$\Delta W \leq 0$	$\Delta W > 0$	Total
Household Non-Retirement Savings (S1)	9036	9237	18273
Net Value of Household Debts (S2)	12204	7989	20193
Household Retirement Savings (S3)	14152	5349	19501
Household Wealth in Fixed Assets (S4)	10099	10760	20859
Financial Wealth, without Retirement Savings (S5)	8291	9125	17416
Financial Wealth, with Retirement Savings (S6)	7451	9010	16461
Overall Household Wealth (S7)	6425	9728	16153

Figure 3: **Histogram of the Job Finding Probabilites in the HRS, 1992-2006**

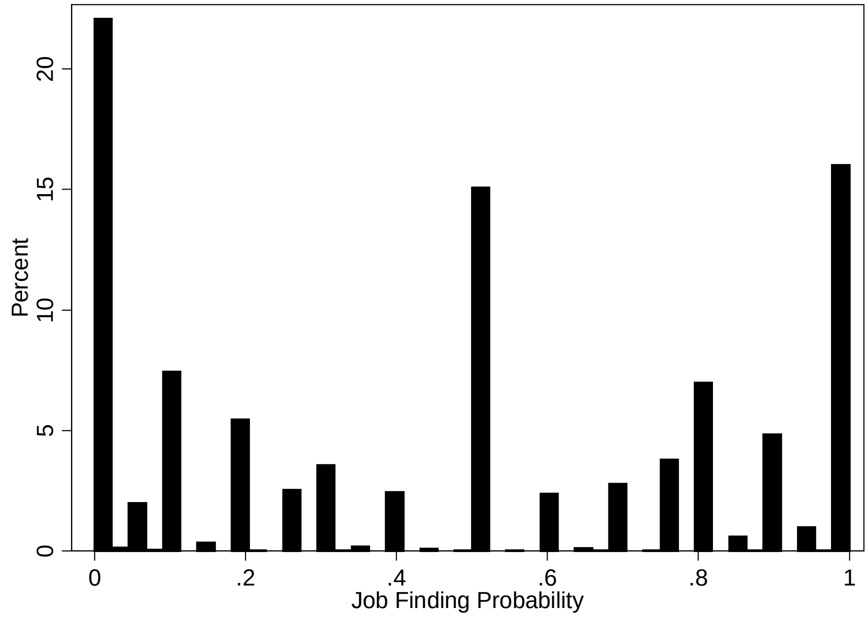

Figure 4: **Two dimensional scatter plot of Financial Wealth between two periods of the HRS, 1992-2004, restricted to wealth<2m$**

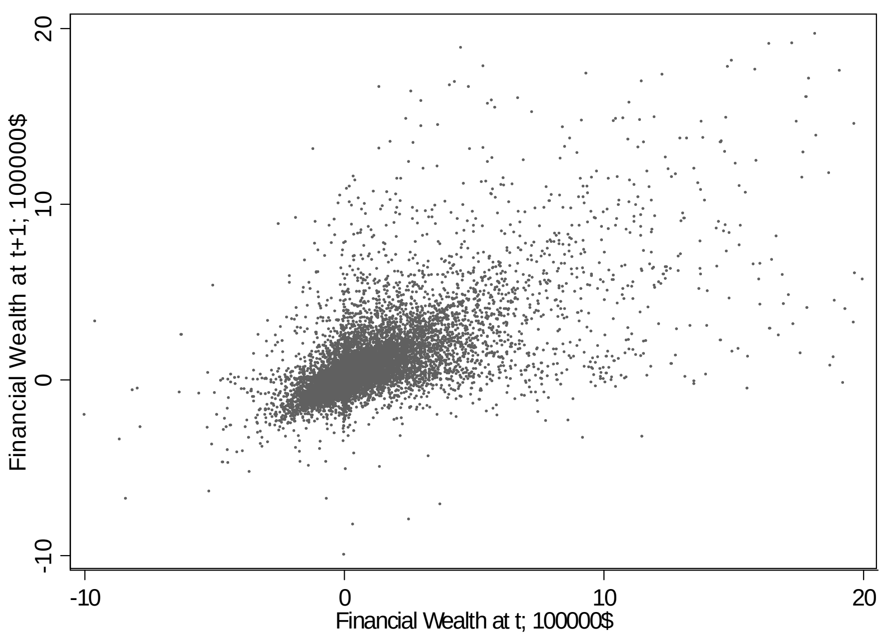

Table 2: **Probability Models for Positive Change in Financial Wealth, without Retirement Savings, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	0.009	0.019	0.023	-0.243	0.006
	[0.017]	[0.017]	[0.017]	[0.199]	[0.030]
P(job-finding)	-0.045	-0.046	-0.047	-0.077	-0.043
	[0.011]***	[0.012]***	[0.012]***	[0.063]	[0.023]*
earnings/100000	0.065	0.013	0	0.003	0.027
	[0.010]***	[0.014]	[0.014]	[0.016]	[0.031]
displaced	-0.031	-0.031	-0.032	0.009	-0.013
	[0.017]*	[0.017]*	[0.018]*	[0.033]	[0.028]
job-leaver	-0.01	-0.014	-0.013	-0.004	-0.016
	[0.010]	[0.010]	[0.010]	[0.012]	[0.016]
female		-0.014	-0.014	-0.012	
		[0.011]	[0.011]	[0.011]	
black		-0.058	-0.058	-0.052	
		[0.013]***	[0.013]***	[0.013]***	
hispanic		-0.027	-0.026	-0.022	
		[0.017]	[0.017]	[0.019]	
ged exam		0.055	0.053	0.062	
		[0.022]**	[0.022]**	[0.023]***	
high school		0.06	0.06	0.058	
		[0.014]***	[0.014]***	[0.014]***	
some college		0.062	0.059	0.06	
		[0.016]***	[0.016]***	[0.016]***	
college or more		0.073	0.066	0.069	
		[0.018]***	[0.018]***	[0.018]***	[0.000]
single		-0.008	-0.002	-0.007	0.025
		[0.010]	[0.010]	[0.010]	[0.036]
second job		-0.006	-0.009	-0.003	0.031
		[0.013]	[0.013]	[0.013]	[0.025]
constant	0.514	0.49		0.539	0.564
	[0.012]***	[0.024]***		[0.034]***	[0.157]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	13979	13979	13979	13979	13979
R-square	0.004	0.018		0.001	0.05

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

[a] marginal effects at the mean

[b] The probability variables are instrumented with tenure and industry dummies

Table 3: **Probability Models for Positive Change in Financial Wealth, with Retirement Savings, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	0.009	0.022	0.026	0.005	0.024
	[0.018]	[0.018]	[0.018]	[0.207]	[0.030]
P(job-finding)	-0.05	-0.049	-0.05	-0.199	-0.046
	[0.012]***	[0.012]***	[0.012]***	[0.064]***	[0.023]**
earnings/100000	0.091	0.033	0.023	0.03	0.024
	[0.012]***	[0.014]**	[0.015]	[0.016]*	[0.032]
displaced	-0.029	-0.029	-0.03	-0.02	-0.013
	[0.018]	[0.018]	[0.018]	[0.033]	[0.028]
job-leaver	0.001	-0.001	0	0.002	0.008
	[0.010]	[0.010]	[0.011]	[0.013]	[0.017]
female		-0.009	-0.008	-0.011	
		[0.011]	[0.011]	[0.012]	
black		-0.078	-0.079	-0.077	
		[0.013]***	[0.013]***	[0.014]***	
hispanic		-0.057	-0.057	-0.065	
		[0.018]***	[0.018]***	[0.020]***	
ged exam		0.038	0.036	0.039	
		[0.023]*	[0.023]	[0.024]	
high school		0.064	0.064	0.064	
		[0.015]***	[0.015]***	[0.015]***	
some college		0.065	0.062	0.068	
		[0.016]***	[0.016]***	[0.017]***	
college or more		0.088	0.081	0.086	
		[0.019]***	[0.018]***	[0.019]***	
single		-0.024	-0.019	-0.025	0.019
		[0.010]**	[0.010]*	[0.010]**	[0.037]
second job		-0.01	-0.012	-0.004	0.029
		[0.013]	[0.014]	[0.014]	[0.026]
constant	0.533	0.518		0.571	0.579
	[0.013]***	[0.025]***		[0.035]***	[0.155]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	13089	13089	13089	13089	13089
R-square	0.008	0.026		0.014	0.072

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

[a] marginal effects at the mean

[b] The probability variables are instrumented with tenure and industry dummies

Table 4: **Probability Models for Positive Change in Overall Household Wealth, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	0	0.006	0.009	0.027	0.005
	[0.018]	[0.017]	[0.018]	[0.204]	[0.030]
P(job-finding)	-0.024	-0.025	-0.025	-0.177	-0.029
	[0.012]**	[0.012]**	[0.012]**	[0.064]***	[0.023]
earnings/100000	0.088	0.041	0.029	0.039	0.004
	[0.014]***	[0.017]**	[0.014]**	[0.018]**	[0.032]
displaced	-0.035	-0.036	-0.037	-0.032	-0.023
	[0.018]**	[0.018]**	[0.018]**	[0.033]	[0.029]
job-leaver	-0.032	-0.033	-0.033	-0.031	-0.012
	[0.010]***	[0.010]***	[0.011]***	[0.013]**	[0.017]
female		-0.01	-0.009	-0.013	
		[0.011]	[0.011]	[0.012]	
black		-0.076	-0.078	-0.075	
		[0.013]***	[0.013]***	[0.014]***	
hispanic		-0.048	-0.049	-0.058	
		[0.017]***	[0.018]***	[0.019]***	
ged exam		0.05	0.046	0.05	
		[0.023]**	[0.022]**	[0.024]**	
high school		0.06	0.058	0.06	
		[0.015]***	[0.014]***	[0.015]***	
some college		0.07	0.064	0.073	
		[0.016]***	[0.016]***	[0.016]***	
college or more		0.105	0.097	0.102	
		[0.018]***	[0.018]***	[0.019]***	
single		-0.027	-0.023	-0.028	0.062
		[0.010]***	[0.010]**	[0.010]***	[0.037]
second job		0.004	0.002	0.01	0.03
		[0.013]	[0.014]	[0.013]	[0.026]
constant	0.572	0.558		0.605	0.661
	[0.013]***	[0.025]***		[0.035]***	[0.151]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	12885	12885	12885	12885	12885
R-square	0.008	0.03		0.018	0.064

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

[a] marginal effects at the mean

[b] The probability variables are instrumented with tenure and industry dummies

Table 5: **Probability Models for Positive Change in Household Non-Retirement Savings**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	-0.029	-0.016	-0.016	-0.223	-0.012
	[0.017]*	[0.017]	[0.017]	[0.194]	[0.029]
P(job-finding)	-0.022	-0.02	-0.02	-0.032	-0.023
	[0.011]*	[0.011]*	[0.012]*	[0.062]	[0.023]
earnings/100000	0.086	0.048	0.053	0.041	0.063
	[0.011]***	[0.013]***	[0.014]***	[0.014]***	[0.031]**
displaced	-0.036	-0.033	-0.034	-0.003	-0.014
	[0.017]**	[0.017]**	[0.017]**	[0.032]	[0.028]
job-leaver	-0.015	-0.016	-0.017	-0.008	-0.026
	[0.010]	[0.010]	[0.010]*	[0.012]	[0.016]
female		-0.006	-0.005	-0.003	
		[0.011]	[0.011]	[0.011]	
black		-0.074	-0.075	-0.07	
		[0.012]***	[0.013]***	[0.013]***	
hispanic		-0.07	-0.071	-0.065	
		[0.017]***	[0.017]***	[0.019]***	
ged exam		0.068	0.071	0.073	
		[0.022]***	[0.022]***	[0.022]***	
high school		0.084	0.086	0.082	
		[0.014]***	[0.014]***	[0.014]***	
some college		0.075	0.078	0.073	
		[0.015]***	[0.015]***	[0.016]***	
college or more		0.08	0.083	0.077	
		[0.017]***	[0.018]***	[0.018]***	
single		-0.016	-0.017	-0.015	0.049
		[0.010]*	[0.010]*	[0.010]	[0.036]
second job		0.011	0.012	0.013	0.011
		[0.013]	[0.013]	[0.013]	[0.025]
constant	0.473	0.473		0.507	0.491
	[0.012]***	[0.024]***		[0.033]***	[0.148]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	14515	14515	14515	14515	14515
R-square	0.007	0.022		0.012	0.007

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.
[a] marginal effects at the mean
[b] The probability variables are instrumented with tenure and industry dummies

Table 6: **Probability Models for Positive Change in the Net Value of Household Debts, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	0.043	0.039	0.05	-0.092	0.034
	[0.016]***	[0.016]**	[0.016]***	[0.184]	[0.023]
P(job-finding)	-0.005	-0.023	-0.026	-0.014	-0.037
	[0.010]	[0.010]**	[0.011]**	[0.054]	[0.018]**
earnings/100000	0.068	-0.024	-0.062	-0.029	-0.024
	[0.011]***	[0.021]	[0.013]***	[0.023]	[0.023]
displaced	-0.063	-0.053	-0.058	-0.034	-0.042
	[0.015]***	[0.015]***	[0.016]***	[0.031]	[0.022]*
job-leaver	-0.012	-0.006	-0.001	-0.001	-0.001
	[0.009]	[0.009]	[0.009]	[0.011]	[0.013]
female		0.002	0.005	0.003	
		[0.009]	[0.010]	[0.010]	
black		0.008	0.004	0.01	
		[0.011]	[0.012]	[0.012]	
hispanic		-0.011	-0.011	-0.007	
		[0.016]	[0.016]	[0.017]	
ged exam		0.086	0.088	0.089	
		[0.020]***	[0.022]***	[0.020]***	
high school		0.054	0.057	0.053	
		[0.013]***	[0.014]***	[0.013]***	
some college		0.073	0.072	0.072	
		[0.014]***	[0.015]***	[0.015]***	
college or more		0.087	0.08	0.085	
		[0.018]***	[0.017]***	[0.019]***	
single		-0.033	-0.022	-0.032	0
		[0.011]***	[0.009]**	[0.011]***	[0.029]
second job		0.003	-0.006	0.003	0.034
		[0.012]	[0.012]	[0.012]	[0.020]*
constant	0.403	0.374		0.39	0.356
	[0.011]***	[0.023]***		[0.030]***	[0.122]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	16208	16208	16208	16208	16208
R-square	0.006	0.051		0.046	0.121

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.
[a] marginal effects at the mean
[b] The probability variables are instrumented with tenure and industry dummies

Table 7: **Probability Models for Positive Change in Household Retirement Savings, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	-0.02	0.008	0.013	0.412	-0.018
	[0.014]	[0.013]	[0.015]	[0.165]**	[0.019]
P(job-finding)	-0.019	-0.02	-0.019	-0.241	0.014
	[0.009]**	[0.009]**	[0.010]*	[0.053]***	[0.015]
earnings/100000	0.215	0.075	0.062	0.085	0.043
	[0.018]***	[0.015]***	[0.011]***	[0.017]***	[0.025]*
displaced	0.02	0.024	0.022	-0.03	0.03
	[0.014]	[0.014]*	[0.016]	[0.028]	[0.019]
job-leaver	0.038	0.038	0.039	0.027	0.038
	[0.009]***	[0.008]***	[0.009]***	[0.010]***	[0.012]***
female		-0.003	0	-0.011	
		[0.009]	[0.009]	[0.010]	
black		-0.113	-0.126	-0.119	
		[0.009]***	[0.009]***	[0.010]***	
hispanic		-0.115	-0.118	-0.138	
		[0.012]***	[0.012]***	[0.014]***	
ged exam		-0.005	0.02	-0.016	
		[0.015]	[0.021]	[0.017]	
high school		0.047	0.082	0.048	
		[0.010]***	[0.014]***	[0.010]***	
some college		0.077	0.117	0.086	
		[0.011]***	[0.016]***	[0.012]***	
college or more		0.128	0.164	0.129	
		[0.014]***	[0.018]***	[0.015]***	
single		-0.047	-0.051	-0.05	0.002
		[0.008]***	[0.008]***	[0.008]***	[0.024]
second job		-0.009	-0.008	-0.001	0.001
		[0.011]	[0.011]	[0.012]	[0.017]
constant	0.226	0.251		0.265	0.276
	[0.011]***	[0.019]***		[0.029]***	[0.063]***
time dummies	YES	YES	YES	YES	YES
age dummies		YES	YES	YES	YES
occupation dummies		YES	YES	YES	YES
region dummies		YES	YES	YES	YES
wealth variables		YES	YES	YES	YES
N	15296	15296	15296	15296	15296
R-square	0.038	0.104		0.016	0.065

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

[a] marginal effects at the mean

[b] The probability variables are instrumented with tenure and industry dummies

Table 8: **Probability Models for Positive Change in Household Welth in Fixed Assets, 1992-2006**

	Model 1 OLS	Model 2 OLS	Model 3 probit[a]	Model 4 IV[b]	Model 5 FE
P(displacement)	-0.021	-0.012	-0.012	0.092	-0.014
	[0.016]	[0.015]	[0.016]	[0.171]	[0.024]
P(job-finding)	-0.012	-0.021	-0.022	-0.205	-0.019
	[0.010]	[0.010]**	[0.011]**	[0.055]***	[0.019]
earnings/100000	0.107	0.009	0	0.009	-0.019
	[0.015]***	[0.015]	[0.013]	[0.016]	[0.026]
displaced	-0.045	-0.041	-0.044	-0.051	-0.029
	[0.016]***	[0.016]***	[0.017]***	[0.030]*	[0.023]
job-leaver	-0.043	-0.041	-0.043	-0.042	-0.034
	[0.009]***	[0.009]***	[0.010]***	[0.011]***	[0.013]**
female		0	0.001	-0.004	
		[0.010]	[0.010]	[0.010]	
black		-0.081	-0.085	-0.081	
		[0.011]***	[0.012]***	[0.012]***	
hispanic		-0.069	-0.071	-0.083	
		[0.016]***	[0.017]***	[0.017]***	
ged exam		0.026	0.027	0.024	
		[0.020]	[0.021]	[0.021]	
high school		0.045	0.047	0.046	
		[0.013]***	[0.013]***	[0.013]***	
some college		0.064	0.064	0.07	
		[0.014]***	[0.015]***	[0.015]***	
college or more		0.074	0.073	0.073	
		[0.016]***	[0.016]***	[0.016]***	
single		-0.098	-0.1	-0.1	0.002
		[0.009]***	[0.009]***	[0.009]***	[0.029]
second job		0.017	0.018	0.025	0.02
		[0.012]	[0.012]	[0.012]**	[0.021]
constant	0.472	0.456		0.5	0.308
	[0.012]***	[0.022]***		[0.031]***	[0.132]**
time dummies	YES	YES	YES	YES	YES
age dummies	NO	YES	YES	YES	YES
occupation dummies	NO	YES	YES	YES	YES
region dummies	NO	YES	YES	YES	YES
wealth variables	NO	YES	YES	YES	YES
N	16648	16648	16648	16648	16648
R-square	0.02	0.061		0.04	0.022

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.
[a] marginal effects at the mean
[b] The probability variables are instrumented with tenure and industry dummies

Table 9: **One-Year Job Loss Expectations and Displacement between Waves, 1992-2006**

	Displaced between waves		P(job-loss within one year)	
	with job-leavers	no job-leavers	with job-leavers	no job-leavers
tenure:				
0-4	9.9%	13.7%	19.9%	19.3%
4-10	5.5%	6.7%	16.5%	16.6%
10-20	4.2%	5.0%	14.7%	14.6%
20-	2.5%	3.1%	12.4%	12.0%
gender:				
male	5.4%	6.9%	15.5%	15.1%
female	6.4%	8.1%	17.0%	16.3%
race:				
white	6.0%	7.6%	16.0%	15.5%
black	5.4%	6.8%	17.6%	17.3%
education:				
<high school	7.5%	9.8%	18.5%	18.2%
ged exam	7.7%	10.4%	18.2%	18.0%
high school	6.1%	7.7%	16.9%	16.2%
some college	5.9%	7.5%	16.5%	16.2%
college or more	4.3%	5.3%	13.4%	12.8%
age:				
0-50	5.7%	6.9%	18.4%	17.4%
50-60	6.1%	7.3%	16.7%	16.1%
60-70	5.5%	7.6%	15.2%	14.6%
70-80	6.8%	9.2%	15.9%	15.0%
80-	3.9%	5.7%	11.8%	14.0%
veteran status				
no	6.1%	7.6%	16.7%	16.1%
yes	5.5%	7.0%	15.1%	14.9%
marital status:				
married/partered	5.5%	6.9%	15.7%	15.3%
single	6.6%	8.5%	17.2%	16.6%
second job				
no	6.0%	7.7%	16.3%	15.7%
yes	5.0%	6.2%	15.9%	15.8%
Total	5.9%	7.5%	16.3%	15.8%

Table 10: **Determinants of One-Year Job Loss Expectations and Displacement between Waves, 1992-2006**

	Model 1 Displaced	Model 2 P(loss)	Model 3 Displaced	Model 4 P(loss)	Model 5 Displaced	Model 6 P(loss)
constant	0.072	0.177	0.145	0.229	0.102	0.191
	[0.004]***	[0.004]***	[0.007]***	[0.008]***	[0.011]***	[0.011]***
tenure: 4-10			-0.052	-0.032	-0.05	-0.031
			[0.005]***	[0.005]***	[0.005]***	[0.005]***
tenure:10-20			-0.07	-0.053	-0.067	-0.051
			[0.005]***	[0.005]***	[0.005]***	[0.005]***
tenure: 20-			-0.086	-0.07	-0.083	-0.071
			[0.005]***	[0.005]***	[0.005]***	[0.005]***
female			-0.007	0.001	0.005	0.016
			[0.004]*	[0.004]	[0.004]	[0.004]***
black			-0.014	0.014	-0.009	0.02
			[0.004]***	[0.005]***	[0.005]*	[0.005]***
hispanic			0.007	0.021	0.006	0.023
			[0.007]	[0.007]***	[0.007]	[0.008]***
ged exam			-0.005	0.007	0.003	0.011
			[0.010]	[0.009]	[0.010]	[0.010]
high school			-0.014	-0.008	-0.006	-0.004
			[0.006]**	[0.006]	[0.006]	[0.006]
some college			-0.015	-0.013	-0.002	-0.003
			[0.006]**	[0.006]**	[0.007]	[0.007]
college or more			-0.026	-0.034	0.001	-0.005
			[0.006]***	[0.006]***	[0.007]	[0.007]
earnings/100000			-0.002	-0.02	-0.011	-0.027
			[0.005]	[0.004]***	[0.005]**	[0.004]***
second job			-0.006	0.002	-0.002	0.007
			[0.005]	[0.005]	[0.005]	[0.005]
single			0.005	0.006	0.006	0.007
			[0.004]	[0.004]	[0.004]	[0.004]*
time dummies	YES	YES	YES	YES	YES	YES
age dummies			YES	YES	YES	YES
occupation dummies					YES	YES
industry dummies					YES	YES
region dummies					YES	YES
N	21833	21833	21833	21833	21833	21833
R-square	0.002	0.003	0.025	0.025	0.037	0.037

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

Table 11: **Relationship between One-Year Job Loss Expectations and Displacement between Waves, 1992-2006**

	Model 1	Model 2	Model 3	Model 4
		Displaced		
P(loss)	0.152	0.136	0.129	0.128
	[0.009]***	[0.009]***	[0.009]***	[0.009]***
tenure: 4-10		-0.048	-0.046	-0.045
		[0.005]***	[0.005]***	[0.005]***
tenure:10-20		-0.063	-0.06	-0.058
		[0.005]***	[0.005]***	[0.005]***
tenure: 20-		-0.076	-0.074	-0.07
		[0.005]***	[0.005]***	[0.006]***
female		-0.007	0.003	0.004
		[0.004]*	[0.004]	[0.005]
black		-0.016	-0.011	-0.011
		[0.004]***	[0.005]**	[0.005]**
hispanic		0.004	0.003	0.004
		[0.007]	[0.007]	[0.007]
ged exam		-0.006	0.002	0.002
		[0.010]	[0.010]	[0.010]
high school		-0.012	-0.005	-0.005
		[0.006]**	[0.006]	[0.006]
some college		-0.013	-0.001	-0.001
		[0.006]**	[0.006]	[0.007]
college or more		-0.021	0.002	0.001
		[0.006]***	[0.007]	[0.007]
earnings/100000		0.001	-0.007	-0.007
		[0.005]	[0.005]	[0.005]
second job		-0.007	-0.003	-0.002
		[0.005]	[0.005]	[0.005]
single		0.005	0.005	0.004
		[0.004]	[0.004]	[0.004]
constant	0.045	0.113	0.077	0.098
	[0.004]***	[0.007]***	[0.011]***	[0.019]***
time dummies	YES	YES	YES	YES
age dummies		YES	YES	YES
occupation dummies			YES	YES
industry dummies			YES	YES
region dummies			YES	YES
depression dummies				YES
health related dummies				YES
job related opinion variables				YES
N	21833	21833	21833	21833
R-square	0.026	0.044	0.053	0.055

*, ** and *** denote significance at 10, 5 and 1 percent respectively; robust s.e.

Table 12: **Competing Risk Models for Modelling Employment Spells of the Employed at Wave 4, 2000**

	Model 1		Model 2	
	Leaving the job	Displacement	Leaving the job	Displacement
	μ^l	μ^d	μ^l	μ^d
female	0.076	0.194	0.076	0.049
	[0.037]*	[0.085]*	[0.041]	[0.093]
black	0.246	0.454	0.242	0.38
	[0.051]***	[0.123]***	[0.051]***	[0.123]**
hispanic	0.099	0.164	0.098	0.093
	[0.068]	[0.156]	[0.067]	[0.154]
high school	0.017	0.323	-0.018	0.254
	[0.049]	[0.112]**	[0.050]	[0.112]*
some college	-0.064	0.133	-0.12	-0.041
	[0.054]	[0.121]	[0.056]*	[0.126]
college or more	-0.013	0.426	-0.127	-0.004
	[0.056]	[0.131]**	[0.065]	[0.148]
earnings/100000	0.903	1.198	0.84	1.248
	[0.065]***	[0.161]***	[0.066]***	[0.162]***
second job	0.026	0.162	0.023	0.117
	[0.054]	[0.133]	[0.053]	[0.131]
single	-0.088	-0.192	-0.08	-0.165
	[0.042]*	[0.097]*	[0.041]	[0.096]
constant	2.579	3.878	2.788	4.702
	[0.050]***	[0.120]***	[0.076]***	[0.188]***
occupation dummies			YES	YES
industry dummies			YES	YES
σ^l or σ^d	1.013	1.664	0.995	1.611
	[0.014]***	[0.052]***	[0.014]***	[0.050]***
N	4454	4454	4454	4454
$E(\mu)$	2.293	4.662	2.916	4.656

*, ** and *** denote significance at 10, 5 and 1 percent respectively

Table 13: **The Extended Competing Risk Model for Modelling Employment Spells of the Employed at Wave 4, 2000**

	Leaving the job		Displacement	
	μ^l	σ^l	μ^d	σ^d
constant	2.857	1.009	4.522	1.536
	[0.081]***	[0.039]***	[0.218]***	[0.112]***
female	0.069	-0.016	-0.164	-0.153
	[0.042]	[0.029]	[0.146]	[0.099]
black	0.221	-0.034	0.457	0.083
	[0.052]***	[0.042]	[0.212]*	[0.144]
hispanic	0.077	-0.011	0.175	0.082
	[0.071]	[0.058]	[0.257]	[0.185]
high school	-0.068	0.004	0.283	0.032
	[0.057]	[0.041]	[0.172]	[0.120]
some college	-0.164	0.024	0.004	0.05
	[0.064]*	[0.045]	[0.185]	[0.129]
college or more	-0.193	-0.03	0.886	0.671
	[0.071]**	[0.045]	[0.295]**	[0.195]***
earnings/100000	0.834		1.455	
	[0.068]***		[0.189]***	
second job	0.021		0.136	
	[0.053]		[0.133]	
single	-0.081		-0.168	
	[0.041]*		[0.092]	
occupation dummies	YES		YES	
industry dummies	YES		YES	
N	4454		4454	
$E(\cdot)$	2.915	0.993	4.742	1.657

*, ** and *** denote significance at 10, 5 and 1 percent respectively, robust s.e.

Table 14: **The Output of the Expected Survival Model, 1992-2006**

	μ	$ln(\sigma_p)$
constant	1.368	-0.634
	[0.040]***	[0.033]***
tenure	0.237	-0.104
	[0.004]***	[0.003]***
tenure^2	-0.008	0.003
	[0.000]***	[0.000]***
tenure^3	0	0
	[0.000]***	[0.000]***
female	-0.059	-0.031
	[0.015]***	[0.011]***
black	-0.026	-0.077
	[0.018]	[0.014]***
hispanic	-0.05	-0.093
	[0.025]**	[0.019]***
high school	-0.023	0.054
	[0.020]	[0.015]***
some college	-0.052	0.107
	[0.022]**	[0.016]***
college or more	-0.059	0.13
	[0.025]**	[0.019]***
earnings/100000	0.042	0.077
	[0.020]**	[0.015]***
occupation dummies	YES	YES
industry dummies	YES	YES
time dummies	YES	YES
σ_c	0.899	
	[0.025]***	
N	25541	
Log-likelihood	-42333.8	

Figure 5: Realized Survival Funtion at Mean Characteristics based on Table 13, Time Until Displacement

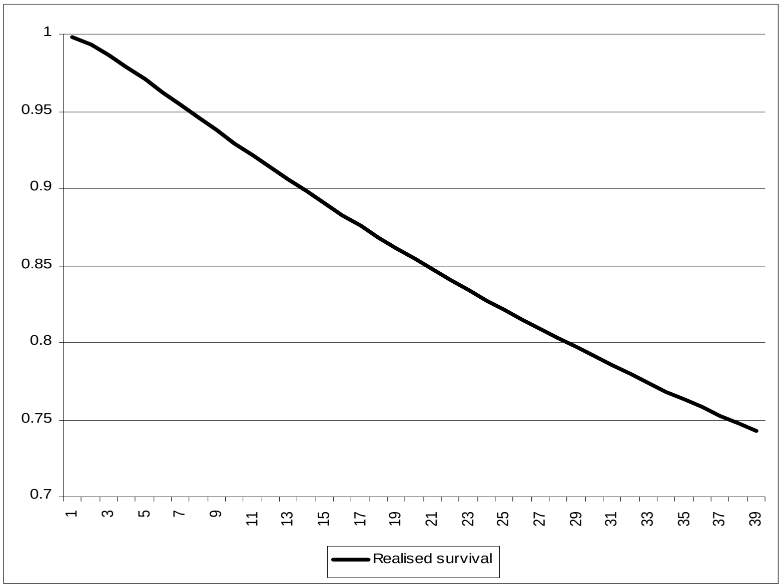

Figure 6: Realized Hazard Funtion at Mean Characteristics based on Table 13, Time Until Displacement

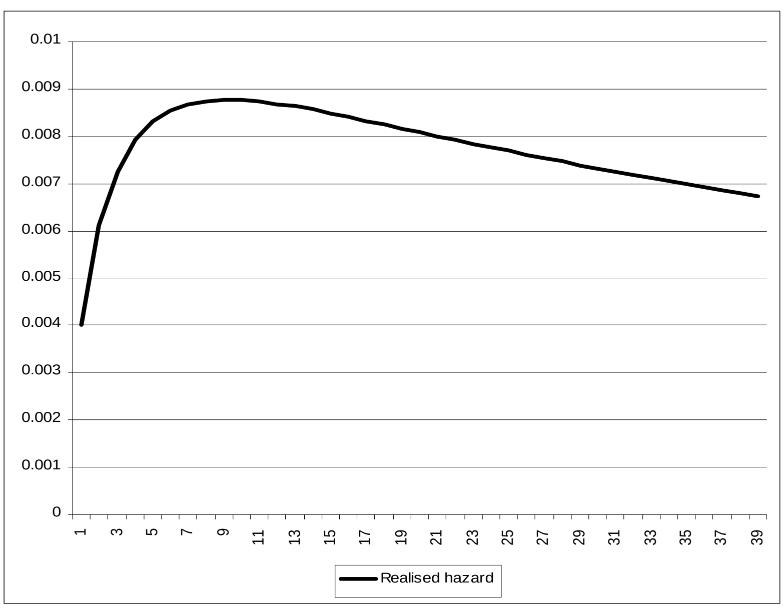

Figure 7: Expected and Realized Survival Funtions at Mean Characteristics based on Table 13 and 14, Time Until Displacement, Broken Down by Tenure

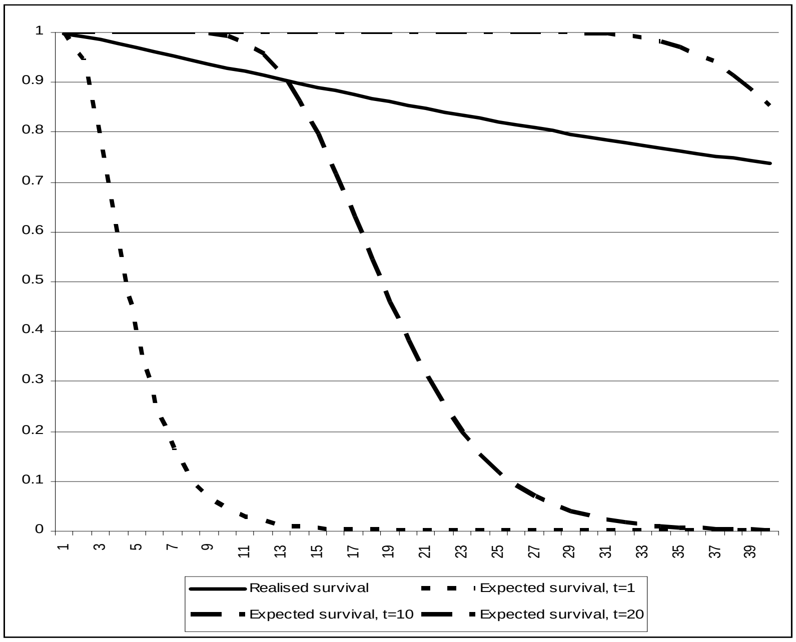

Figure 8: Expected and Realized Survival Funtions at Mean Characteristics based on Table 13 and 14, Time Until Displacement, Broken Down by Tenure and Gender

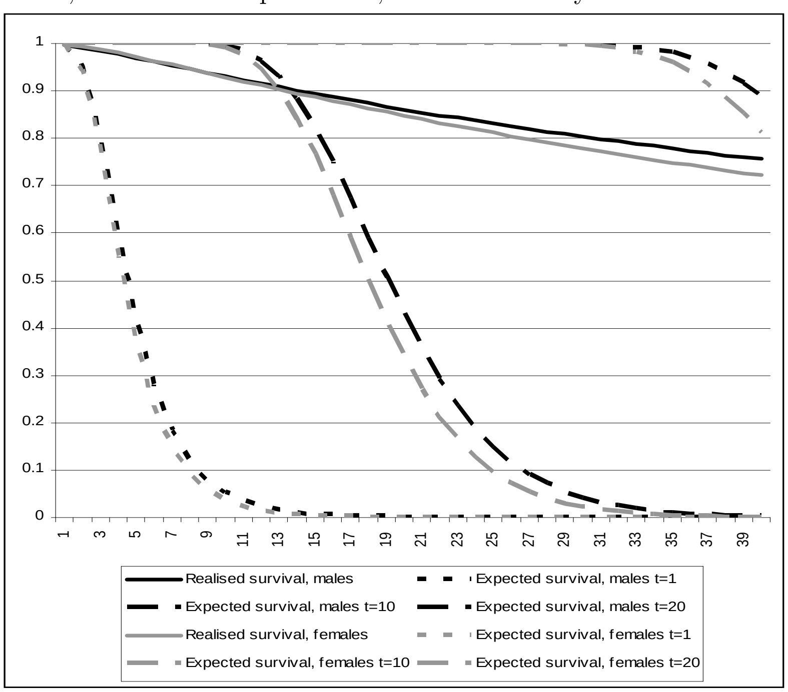

Figure 9: Expected and Realized Survival Funtions at Mean Characteristics based on Table 13 and 14, Time Until Displacement, Broken Down by Tenure and Race

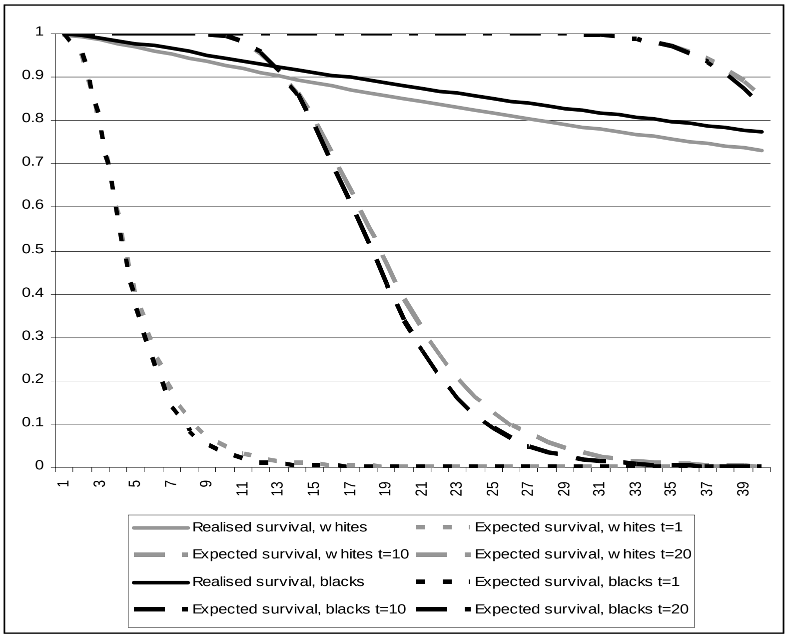

Figure 10: Expected and Realized Survival Funtions at Mean Characteristics based on Table 13 and 14, Time Until Displacement, Broken Down by Tenure and Education