Prediction Errors: Re-employment Expectations and Realizations

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Abstract

We use longitudinal data to investigate several misconceptions of people with respect to their re-employment probability which alter their labor market behavior in a sub-optimal way. People with unemployment experience of more than 3 years significantly underestimate their actual re-employment probabilities. Information about the previous unemployment experience of individuals is the minimum amount of information needed to make more acurate predictions than the individuals themselves. Underestimation is also found to be related to subsequent behavioral changes. People who underestimate their re-employment probability accept a lower wage, work fewer hours, are less likely to work full-time, are more likely to drop out of the labor force and less likely to actively search for a job. This information can be used in job agencies for example to inform clients and prevent adverse behaviour.

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1 Introduction

Drawing conclusions about decision processes from revealed preference data may be difficult if the decision maker is not rational and may only have partial information about all possible outcomes. In that case, data on self-reported expectations may be useful to understand revealed choices and to validate assumptions about expectations (Manski, 2004).

One of the main goals of labor economics is to understand and predict individual choices, for example with respect to labor force participation, occupation, consumption, saving and education. Choices in the labor market are often intertemporal and usually made under uncertainty so that analysing subjective expectations is crucial in understanding the heterogeneity in revealed preferences that is otherwise unexplained. Therefore incorporating expectations into empirical economic models is likely to help us understand otherwise unexplained observed behaviour.

One of the main uncertainties in the labor market context is job security and employability and it is the expectation about these that influences labor market choices. Perception of job security is usually defined in the literature as the expected probability of an employee to loose a job whereas perceptions of employability refer to the subjective probability of obtaining employment within a certain time frame once unemployed. Interestingly, the research in this area is rather scarce although the psychological literature suggests that the observed rise in perceived job insecurity in recent years is associated with lower health (physical and mental) and job satisfaction (Sverke et al. 2002; Cheng and Chan 2008). Most previous papers in this research area have analysed how an employee forms unemployment expectations: what information the expectation is based on. Some have investigated whether the unemployment expectations convey useful information by analyszing whether they are actually related to unemployment experiences. Few have connected unemployment expectations with other labor market outcomes aside from the realization of the expectation itself.

Only a handful of studies have looked at the re-employment expectations for the unemployed, although several studies have shown that unemployment is one of the life events that is associated the strongest with decreases in well-being as measured by subjective self-evaluated life satisfaction questions in surveys. Very little is known about the formation of re-employment probabilities and the divergence in subjective and objective re-employment probabilities for the unemployed. Any discrepancy in these two would likely have significant implications for the well-being of the unemployed, their search behaviour, their reservation wages and might alter these in a sub-optimal way. Misconceptions, i.e. overconfidence, concerning re-employment probabilities might result in insufficient job search effort or unrealistic reservation wages.

To our knowledge, there is no comparable study that explicitly looks at re-employment expectations such as ours. Using data from the German Socio-Economic Panel (SOEP),this paper closes this research gap by investigating whether the unemployed are able to predict their re-employment probabilities accurately or whether there is a divergence between subjective and objective re-employment probabilities. More specifically, this paper investigates the following research questions: (1) How are re-employment expectations formed?, (2) What informational content is in subjective re-employment expectations?, (3) What are the determinants of prediction errors? Who are the people that make prediction errors and how large are the prediction errors?; (4) What critical information about the individuals is needed so that they can make better predictions; (5) Do these prediction errors lead to adverse behavioral changes?

We find that people with unemployment experience of more than 3 years significantly underestimate their actual re-employment probabilities. In fact, our model performs better on average at predicting re-employment than the individuals themselves. The only information needed about the individuals to make a significantly better prediction on average is their previous unemployment experience. Underestimation is also found to be related to subsequent behavioral changes. People who underestimate their re-employment probability seem to accept a lower wage, work fewer hours, are less likely to work full-time, are more likely to drop out of the labor force and less likely to actively search for a job. This information can be used in job agencies for example to inform clients and prevent adverse behaviour.

2 Background

Since the early 1990's questions regarding respondents expectations about certain life events have been added to surveys. (Manski, 2004). Using these new variables, economic research has, for example, analyzed the divergence between subjective life expectancy and actual mortality such as in Hurd and McGarry (2002) or Smith et al. (2001).

In past labour economics research, subjective expectations and their divergence from actual realizations have mainly been analyzed in the context of income expectations such as the studies by Jappelli and Pistaferri (2010), Dominitz and Manski (1997b), Kaufmann and Pistaferri (2009) or Jappelli and Pistaferri (2000).

Another strand of the literature has investigated the subjective perceptions of job insecurity where job insecurity is measured by questions for the employed regarding the subjective job loss expectations and sometimes also by questions on expectations of re-employment in case of a lay-off. Most of these papers have analysed whether unemployment expectations for the employed are related to certain observable characteristics of the individual or job characteristics or whether they largely convey unobserved information.

Previous research found that job insecurity (as measured by unemployment expectations questions and sometimes additional re-employment expectations of the employed) is related to past unemployment experience (also Campbell et al., 2007; Green et al., 2001) and type of employment contract (Green, 2003; Green et al., 2001). Campbell et al. (2007) also finds that unemployment experience of a close friend and other objective indicators of insecure jobs are related to perceived job insecurity. Also unemployment in the external labor market was found to influence individual's unemployment expectations (Green et al., 2000; Linz and Semykina, 2008). Perceptions of job security were found to be higher for women (Green, 2009), for individual's with higher levels of education (Dominitz and Manski, 1997a; Green, 2009; Linz and Semykina, 2008; Manski and Straub, 2000), higher supervisory responsibilities (Linz and Semykina, 2008), more tenure (Bender and Sloane, 1999) and older individuals (Green, 2009; Linz and Semykina, 2008).

There are significantly fewer papers that have actually compared unemployment expectations with actual realization to assess whether subjective unemployment expectations convey useful information. All of these papers found that subjective unemployment expectations are strong predictors of unemployment experiences in the near future even when other job and individual characteristics are accounted for, such as Green (2011), Green et al. (2001), Stephens (2004), Campbell et al. (2007) and Dominitz and Manski (1997a).

Only a handful of studies have analysed perceived employability of the unemployed. Dickerson and Green (2012) mainly look at unemployment expectations but also at re-employment expectations, although in lesser detail. They show that the re-employment expectations are related to finding a job, both for Germany (using the GSOEP) and Australia (using the HILDA). Green (2011) analysed how subjective re-employment probabilities for the unemployed modify the impacts of unemployment on life satisfaction and health for example.

Apart from these findings, little is known about the formation and validity of re-employment expectations. This paper will build on the analysis by Dickerson and Green (2012) in several ways. First, contrary to Dickerson and Green (2012) we use a variable in the GSOEP that specifically asks the unemployed and not the employed about their re-employment expectation. Dickerson and Green (2012) use a variable that asks the employed about their concern of re-employnment in the hypothetical event of a lay-off. They then restrict the sample to individuals who indeed lost their jobs. Hence they have to restrict their sample to individuals with a short time in unemployment and who could be observed in employment prior to the unemployment spell. Furthermore, this variable they use for the analysis with the German data only has categorical outcomes (easy, difficult, almost impossible), although they show using the Australian data that numeric cardinal scales perform better at predicting subsequent re-employment than verbal ordinal scales. These limitations prevent them from exploring re-employment probabilities in more detail.

Second, this paper investigates how re-employment expectations are formed and third who makes prediction errors. This will allow us to draw some important policy conclusions about which people need to be informed about their potential misconception in order to prevent those individuals from basing their labour market decisions and behaviour on these misconceptions.

Another important contribution of this paper will be to investigate the extent to which researchers can make better predictions than the individuals themselves based on objective information readily available about the individuals.

To our knowledge, there is no other comparable study that would explicitly look at re-employment expectations in this manner.

3 Data

The analysis is based on the German Socio-Economic Panel (SOEP). This is a longitudinal representative panel dataset of private households in Germany starting in 1984. The SOEP re-interviews the same private households annually and thereby approximately 11,000 households and 20,000 people are sampled every year. Data from the SOEP is used as it is ideal for analyzing objective and subjective re-employment probabilities because there is information on both. The SOEP collects information on objective characteristics such as education, health or labour force status as well as subjective information like opinions on several domains or life satisfaction.

The focus in this project is on the question concerning subjective expectation about reemployment of the unemployed: How likely is it that you start paid work within the next two years?. The responses range on an 11-point scale from 0 percent to 100 percent.

The years 1999, 2001, 2003, 2005, 2007 and 2009 are used since the subjective re-employment probability is only asked every two years. The two subsequent years will be used to estimate the objective probability that someone will be employed within the next two years after his initial unemployment status. This analysis only focuses on individuals who are observed to be unemployed and between 16 and 64 years of age. Of these 6248 observations, we loose 30 percent of the observations because we do not observe the employment status of the person in time t+1 and t+2. Of the remaining observations, another 33 percent are dropped because they exit the labor market in t+1 or t+2. We apply this restriction because the estimates should not be biased due to anticipated behavioural changes. Looking at subsequent behavioural changes is a topic for future research. Another 33 percent were dropped because the they were defined as not actively looking for work (they reported that they would not be able to immediately take up a suitable position or did not actively seek work within the last 4 weeks). Another 126 observations were dropped because they had previously been self-employed. Of the remaining 2084 observations, we loose 20 percent due to missings in the control variables. This leaves us with 1669 observations.

3.1 Controls

We account for a number of factors that have been found to be important determinants of subjective and objective re-employment prospects. More specifically, we control for similar variables as in Dickerson and Green (2012): (1) socio-demographic characteristics such as gender, age (and its squared) and education; (2) previous unemployment experience (total length of unemployment in years over the respondent's career); and (3) characteristics of the last job such as whether the person was previously working in the private sector, whether the person was temporary employed and information on the size of the company (indicator for 20 or more persons at the previous workplace).

We additionally account for other characteristics of the previous job that are likely to influence subjective and objective re-employment prospects such as last labor income, socio-economic status of the previous job[1] .

We additionally account for the total number of years of work experience of the respondent (full-time and part-time seperately) as well as the local unemployment rate. We also control for a range of other demographic characteristics that are likely to influence subjective and objective re-employment prospects such as marital status, home ownership and whether the respondent has children.

Finally, we also control for individuals' Big 5 personality traits and locus of control which should capture some of the otherwise unobserved heterogeneity in subjective and objective re-employment prospects. It has been shown for example that personality traits related to neuroticism are predictive of labor market outcomes (Almlund et al., 2011). People with an internal locus of control or with higher self-esteeem for example are found to search more for a job (Caliendo et al., 2010). Similarly, conscientiousness, is found to be related to performance and wages (Almlund et al., 2011).

[1] The Standard International Socio Economic Index of Occupational Status (ISEI) measures the socio-economic status of a person. It was developed based on information about income, education, and occupation (7 categories of profession based on the ISCO88 code) by Ganzeboom et al. (1992).

The 2005 and 2009 wave contain questions on the respondent's personality based on the Five Factor Model developed by Costa and McCrae (1992); McCrae and Costa (1985). The five factor model measures five basic psychological dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. A short 15 item version is implemented in the SOEP based on the 25 item measure by John et al. (1991) (Gerlitz and Schupp, 2005). Each of the five components of the five factor model is represented by three items. Gerlitz and Schupp (2005) show the internal consistency and validity of the short version. We confirm the five component structure by conducting a principal component analysis for the years 2005 and 2009, restricting the principal component analysis to finding 5 components.[2] Each of the components indeed represents one of the five personality factors with the three relevant items loading highly on the relevant factor. We follow Gerlitz and Schupp (2005) and predict the first five components for the years 2005 and 2009. We then average over 2005 and 2009 if information in both waves is available to reduce measurement error. The final variables are standardized over 2005 and 2009 to have mean 0 and standard deviation 1.

Locus of control is a psychological concept capturing individuals beliefs about the extent to which future outcomes are determined by his or her own actions as opposed to external factors. Those with an external locus of control generally believe that what happens to them in life is due to external factors (e.g. fate, luck, other people, etc.) while those with an internal locus of control believe that their own actions determine to a large extent what happens to them in life (Rotter, 1966). Questions on locus of control were asked in 1994-1996, 1999, 2005 and 2010. However, the locus of control items are not consistent over time. We therefore use the 2005 and 2010 locus of control questions only that fall into the analysis period and which are consistent over time. After rescaling the variables so that they are increasing in internal control tendencies, principal component analysis is conducted for the years 2005 and 2010. We then average over 2005 and 2010 if information in both waves is available to reduce measurement error. The final variables are standardized over 2005 and 2010 to have mean 0 and standard deviation 1.

[2] We reverse the scores of the 7-point Likert scale for some items as in Heineck and Anger (2010) so that a higher score corresponds to the relevant personlity type

4 Expectation Formation

4.1 Estimation Strategy

In a first step, the analysis examines how expectations are formed:

$$\begin{aligned} SubProb_{it} &= \alpha + X'_{it}\beta + \varepsilon_{it} \\ \varepsilon_{it} &= \mu_i + \nu_{it} \end{aligned} \tag{1}$$

where the dependent variable is the subjective self-reported re-employment probability for the unemployed, X'_{it} represents a vector of control variables (consisting of socio-demographic characteristics, labor market history, external labor market characteristics, previous job characteristics and personality traits as explained in the previous section), ε_{it} is a composite error term that consists of an individual-specific random effect μ_i and an idiosyncratic error ν_{it}. Standard logit models are estimated as well as correlated random effects models, in which μ_i is allowed to be correlated with the explanatory variables of the form $\mu_i = \overline{x_i}\eta + \vartheta_{it}$ (Mundlak, 1978) in order to control for unobserved heterogeneity. This first step provides information on what objective information individuals form their re-employment expectation.

4.2 Results

We estimate 3 specifications as shown in Table 1: (1) an OLS model, (2) an OLS model with random effects and (3) a correlated random effects model. Several socio-demographic variables are found to be related to a perceived higher re-employment probability if unemployed. The strongest relationship is found for gender: Men on average expect a 6 percentage points (p.p.) higher probability of re-employment than women. This relationship holds even if we control for fixed unobserved heterogeneity in column (3). A positive relationship of similar size is also found for years in education. The positive association between home ownership and the perceived re-employment probability disappears once we move to the random effects model. Similarly, the negative association between marriage and the perceived re-employment probability disappears once we control for the individual-specific averages of the control variables, suggesting that these variables are correlated with some fixed unobserved characteristic. We also find a significant relationship between age and the perceived re-employment probability which is inversely u-shaped (maximum of approximately 30 and negative effects starting at around age 55).

[Insert Table 1 here]

The labor market history variable that is associated the strongest with the perceived re-employment probability is the previous unemployment experience. People with an unemployment experience accumulated over their life time of about 5 or more years expect a 10 pp. lower re-employment probability than individuals without previous unemployment experience (column 3). Full-time and part-time work experience are positively related to the re-employment probability, although only weakly (and insignificant in the correlated random effects specification as stanard errors are high). Having 10 or more years of tenure is associated with lower expected re-employment probabilities of around 7.7 pp. (significant, column 1) to 0.5 pp. (insignificant, column 3).

Although a higher unemployment rate in general is found to be associated with lower re-employment expectations, this result seems to be driven by unobservables as the coefficient becomes small and insignificant in the correlated random effects specification.

Interestingly, many of the characteristics of the previous workplace do not seem to influence the expected re-employment probability. Agriculutural/craft workers (machine operators) are significantly more optimistic than those in elementary occupations as they have a 8 pp. (17 pp.) higher re-employment expectation.

Personality traits are strongly and significantly correlated with re-employment expectations. A 1 standard deviation increase in openess to experiences is associated with a 2 pp. higher re-employment expectations; a 1 standard deviation increase in agreeability with a 1.7 pp. lower re-employment probability and a 1 standard deviation increase in locus of control with a 1.7 pp. higher re-employment probability.

5 Expectations and Realizations

5.1 Estimation Strategy

In a second step, we will investigate whether an individuals' subjective re-employment expectation is related to the actual realization. Therefore the following logit model is estimated where the dependent variable is a binary indicator that equals 1 if the individual is observed to be employed in $t+1$ and/or $t+2$:

$$Pr(employed_{t+1,t+2} = 1|X) = \Delta(\alpha_1 + W'_{it}\delta + X'_{it}\beta + \varepsilon_{it}) \tag{2}$$

where W'_{it}represents a vector of five dummy variables for the subjective re-employment probability (10-20%, 30-40%, 50-60%, 70-80%, 90-100%). Including control variables X'_{it} allows one to make statements about whether the subjective re-employment probabilities reported by the respondents offer any additional information over and above the observed characteristics of the individual. In other words, one can answer the question whether individuals know more about their re-employment than what researchers can observe.

In a further step, the analysis will investigate whether individuals on average are better at predicting their re-employment or whether we as researchers can make better predictions based on the observables (excluding the self-reported subjective re-employment probabilities). We will therefore compare prediction-realization tables for the subjective predicted self-reported information and for the model based predicted probabilities (prediction of the dependent variable in equation (2)). Prediction-realization tables compare the prediction from a model with the actual realization.

As the percentage of total predictions can be misleading if one of the outcomes is particularly likely (Veall and Zimmermann, 1992), we will adopt a method suggested by Veall and Zimmermann (1992) who show that to measure performance, McFaddens σ_n (McFadden et al., 1977), performs best:

$$\sigma = p_{11} + p_{22} - p_{.1}^2 - p_{.2}^2 \tag{3}$$

$$\sigma_n = \sigma/(1 - p_{.1}^2 - p_{.2}^2) \tag{4}$$

where p_{ij} are the entries of the prediction-realization table with expectation j and realization i. The number $p_{.i}$ represents the fraction of times alternative i is predicted. As the realization is binary (employed/unemployed), we employ several alternative cut-off values to transform the subjective re-employment probability and the model based predicted probability from equation (2) into a binary variable and calculate σ_n for all alternative prediction-realization tables.

We then determine the minimum amount of information that is needed about an individual to be able to make a more accurate prediction about the individuals future prospects than the individual is able to make himself. This will be done by calculating σ_n for all possible combinations of control variables and finding the combination that produces a $\sigma_n$that is (significantly) larger than the σ_n for the prediction-realization table based on the self-reported expectation.

5.2 Results

Table 2 shows the results of the labor force status model where the dependent variable is a binary variable that equals 1 if the respondent is employed in t+1 and/or t+2 and 0 otherwise.

The first column just controls for the self-reported re-employment expectations. The higher the expectation, the higher the actual re-employment probability. People with an expectation of 70 to 80% for example, have a 23 pp. higher re-employment probability than people who do not expect to be re-employed in the near future.

Column (2) controls for the same or very similar variables as in Dickerson and Green (2012). This reduces the size of the effects and only an expected re-employment probability of 90 to 100% (compared to a re-employment expectation of 0%) remains to be significantly associated with actual re-employment in the future.

We move to column (3) where we control for a more extensive set of information about the individual's characteristics as described in section 3.1. This furthermore reduces the size of the coefficient for a 90 to 100% re-employment expectation, although not significantly. Controlling for random effects in specification (4) reduces the size of the coefficient even more. The coefficient becomes very small and insignificant in column (5) when we estimate the correlated random effects model where the individual specific means of the control variables are included to reduce unobserved heterogeneity in the estimates.

[Insert Table 2 here]

These results indicate that the additional information the subjective perceptions hold are fairly limited. Once a basic set of controls is added, there is only additional information in statements about a 90 to 100% re-employment expectation. This effect seems to be correlated with some unobserved fixed characteristics correlated with some of the control variables.

The measures of fit statistics at the end of the table also indicate that the model fit could be increased due to the inclusion of further controls as well as random effects and correlated random effects (McKelvey and Zavoina's R2 increases from 0.146 to 0.530 for example).

Figure 1 graphs the actual re-employment probability (on the vertical axis) against the ordinal response categories of the self-reported probability (blue line), and the predictions of specifications (2) to (5) of the labor force status model (excluding the self-reported expectations in the prediction). The dashed line is the 45 degree line and denotes perfect prediction. The black line is our preferred prediction from the correlated random effects model and it can be seen that is is very close to the 45 degree line. The prediction from the other specifications seem to perform reasonably well for re-employment probabilities of 30% and above, but are less acurate at the lower end of the distribution. Especially moving from specification (3) to specification (4) where we also control for personality traits, improves the fit at the low end of the distribution.

[Insert Figure 1 here]

The blue line lies above the 45 degree line for self-reported probabilities of 50% and below indicating that there are some people who consistently seem to underestimate their re-employment probability. The bottom part of Figure 1 shows the self-reported probability and the prediction from specification (5) from the top part of the graphic but including confidence intervals. This shows that at the bottom of the distribution our prediction is often significantly better than the perception of the individuals themselves (where the confidence intervals do not overlap). In any case, the 45 degree line lies within the confidence interval of our prediction based on specification (5) from Table 2, suggesting that our model on average is able to make better predictions than individuals themselves.

We test this formally as presented in Table 3 by comparing prediction-realization tables for subjective self-reported expectations with the different predictions of our specifications in Table 2. This allows calculating McFaddens σ_n (McFadden et al., 1977) which indicates the performance of the prediction. In order to do so, the ordered response categories of the self-reported expectations as well as the predictions from our labor force model (excluding the self-reported expectations as regressors) have to be recoded to a binary 0/1-variable to compare the prediction with the actual realization in t+1 and t+2 which is also a binary variable (employed vs. unemployed). We choose a cutoff value of 60% to do so, so that values of 60 and above are assumed to be expectations for future employment whereas values below 60 are assumed to be expectations of unemployment.

[Insert Table 3 here]

Sensitivity tests around this cutoff value were conducted where σ_n for all possible prediction-realization tables for all different cutoff values for the predictions were calculated as shown in Appendix Table A2 (for the self-reported probability) and A3 (for the prediction based on the correlated random effects model). Appendix Table A4 and A5 report an adjusted σ_n, where σ_n is multiplied by n^2/N^2 – the squared proportion of used observations in the prediction-realization-table compared to the total number of observations – in order to adjust for the fact that dependent on the cutoff value not all observations are used. The tables show that adjusted σ_n is maximixed at our chosen cutoff value of 60.

The numbers in the first two rows in Table 3 show the fraction of correct predictions for each combination of realization i (0=unemployed, 1=employed) and expectation j (0=unemployed, 1=employed). The row below that shows the performance measure σ_n with the 95% confidence interval in square brackets.

Table 3 shows that even σ_n for the predictions from the baseline model is higher – although not significantly higher – than σ_n for the self-reported expectations. Once we include personality traits in the model for the prediction as in specification (4) of Table 2, the performance measure is significantly higher indicating that our model on average can predict the individuals' future labor market outcomes better than the individual's themselves. McFaddens's σ_n is especially high for the preediction from the correlated random effects model of specification (5) in table 2 (5.57 compared to 0.30).

The conclusions remain the same when we consider another performance measure as a sensitivity check in the last two rows, δ_n, which was shown to perform second to McFaddens σ_n (Veall and Zimmermann, 1992).[3]

We rerun the correlated random effects labor force model with every possible combination of control variables and calculate σ_n for all estimation results to find the minimum amount of information needed about the individual to make a better prediction on average than the individuals themselves. The top part of Table 4 shows that there is one variable needed to make a significantly better prediction than the individuals themselves and that is the previous unemployment experience (Panel A). Panel B shows all combinatons of two variables to achieve a significantly better prediction. A significantly better prediction cannot be achieved with two variables without the unemployment experience. Panel 3 shows that a mimimum of three variables are needed if one wants to achieve a better prediction than the individuals' perception without using the unemployment experience as a control variable. Although the absolute value of σ_n (0.313) is higher than the value of σ_n for the subjective perceptions (0.304), the difference is not significant.

[Insert Table 4 here]

We have established that some individuals underestimate their re-employment probabilities and that on average we are able to make more acurate prediction about their re-emloyment if we simply knew the individuals' past unemployment experience. In order to draw some policy recommendations from this exercise and to assist individuals in making better predictions, one has to identify the people who are more susceptible to making these errors than others.

[3] $\delta = (p_{11}p_{22} - p_{12}p_{21})/[(p_{11} + p_{12})(p_{21} + p_{22})]$ as in Veall and Zimmermann (1992).

6 Determinants of Prediction Errors

6.1 Estimation Strategy

We estimate an ordered logit model where the dependent variable y_j has 3 categories (i=underestimation, exact estimation and over estimation) and X_{it} is a set of control variables as described in Section 3.1:

$$Pr(y_j = i) = Pr(\kappa_{i-1} < \alpha_1 + X'_{it}\beta + \varepsilon_{it} \leq \kappa_i) \tag{5}$$

.

This will provide insight about the group of people that potentially need to be informed about their re-employment prospects to counteract adverse effects of this misconception on their behaviour.

Underestimation means that someone did not think he would be re-employed within the next two years (expectation of 50% or below), but was actually re-employed within the next two years; overerestimation means that the person thought he would be re-employed (expectation of 60% or above) whereas he actually was not and exact estimation occurs if someone thought he would get a job and did get a job or did not expect to get a job and indeed was still unemployed two years later.

As the previous analysis could not tell us anything about the actual size of the prediction error, we next move on to investigate who is susceptible to making especially big errors. This is done by calculating the difference between the subjective self-reported re-employment expecation and the objective re-employment expectation based on the prediction of the labor force model specification (5) (excluding the subjective expectations). As was shown in Graph 1 and the previous analysis, this prediction performs very well in predicting re-employment. Hence we assume that this prediction is equal to the underlying true re-employmet probability.

We investigate the determinants of the prediction error along the entire prediction error distribution as we suspect there could be differential effects dependent on whether you are at the top of the distribution and overestimated the re-employment probability or at the bottom and underestimated re-employment chances.

We apply the unconditional quantile regression method recently developed by Firpo et al. (2009) in order to estimate marginal effects at various quantiles of the overall prediction error distribution. This allows us to interpret the marginal effects with respect to the prediction error distribution $F(\textit{prediction error})$ and not the the distribution of prediction errors conditional on prediction error determinants X as in the classic conditional quantile regression developed by Koenker and Bassett (1978) : $F(\textit{prediction error}|X) = F(\epsilon)$.[4]

The method by Firpo et al. (2009) uses a "recentered influence function" to essentially reweight the dependent variable so that the mean of the reweighted variable corresponds to the quantile of interest. This then allows OLS to be applied directly to the reweighted dependent variable.[5]

The recentered influence function (IF) at each quantile τ of the distribution of Y is defined as:

$$\mathrm{IF}(Y; q_\tau) = (\tau - \mathbf{1}\{Y \leq q_\tau\})/f_Y(q_\tau), \tag{6}$$

where q_τ is the value of the cummulative distribution of Y at the τth quantile and $f_Y(\cdot)$ is the marginal density function of Y. The recentered influence function simply recenters the influence function so that its mean corresponds the distribution value at the percentile of interest. Specifically,

$$RIF(Y; q_\tau) = q_\tau + \mathrm{IF}(Y; q_\tau). \tag{7}$$

Unconditional quantile regression involves estimating the expectation of the recentered influence function conditional on a set of covariates X, i.e. $E[\mathrm{RIF}(Y; q_\tau)|X])$. For simplicity, a linear relationship between the two is typically assumed so that we can estimate the following unconditional quantile regression:

$$E[\mathrm{RIF}(\textit{prediction error}_{it}; q_\tau)|X_{it}] \quad = \quad X'_{it}\beta^\tau + \epsilon^\tau_{it}. \tag{8}$$

[4]This distinction is important as someone's conditional prediction error quantile may change as covariates change (Froehlich and Melly, 2010). Furthermore, someone who is in the 50th percentile of the prediction error distribution conditional on their IQ and other characteristics might be in the 75th percentile of the overall prediction error distribution distribution (Borah and Basu, 2013).

[5]All estimation is done using the RIF-Regression STATA ado file from Firpo, Fortin and Lemieux (2009), which can be downloaded at http://faculty.arts.ubc.ca/nfortin/datahead.html.

6.2 Results

The results of an ordered logit model where the dependent variable y_j has 3 categories (i=underestimation, exact estimation and over estimation) are presented in Table 5. Six variables can be identified that are related to making prediction errors. The first one is gender. It was shown in Section 4 that men were very positive with respect to their re-employment chances. Table 5 now shows that they seemed to be overly optimistic as being male is related to a 2.8 pp. higher probability of overestimating the re-employment probability compared to women.

Married people have a 8.7 pp. and home owners a 3.7 pp. higher probability of underestimating their re-employment probability. Interestingly, people with an unemployment experience of 3 to 5 years have a 9 pp. higher probability of underestimating compared to people with no unemployment experience. Also people who were previously temporary employed (4.7 pp.) are more likely to underestimate their re-employment probability as well as managers/professionals (19.8 pp.) and technicians and associated professions (12.0 pp.) compared to people in elementary occupations.

People who are more agreeable are also more likely to underestimate their re-employment probability (a 1 std. dev. increase in agreeability increases the probability to underestimate by 2.2 pp.).

[Insert Table 5 here]

Table 6 provides more information on the determinants of the size of the prediction error at various points of the prediction error distribution. The prediction error was caclulated by subtracting the subjective re-employment expectation from the model based predicted re-employment probability (from Table 2 specification (5), excluding the subjective expectations as predictors). Hence, the higher the prediction error, the more the person underestimated the re-employment probability. The more negative the prediction error, the more the person overestimated the re-employment probability.

Being married contributes to underestimating the re-employment probability along the entire prediction error distribution. Having children contributes to an overestimation of the re-employment probability, especially among those at the 25th quantile (those who severely overestimate their re-employment probability). Similarly, home ownership contributes to an overestimation at the 25th quantile.

Big contributors to underestimation along the entire distribution are having previously worked as a manager/professional, technichian or associate profession or as a clerk (14 pp. to 55 pp. increase in prediction error).

Neuroticism reduces wheres agreeability increases underestimation. Locus of control contributes to overestimation among those who severely overestimated.

[**Insert Table 6 here**]

Interestingly, having unemployment experience of 3 to 5 years increases the size of the prediction error by 29 pp. among those who severely underestimate their re-employment probability. However, having lots of unemployment experience (5 years or more) also increases the probability of overestimating the re-employment probability among those who severely overestimated their re-employment probability.

Therefore there seem to be two types of people onto which the the unemployeemnt experience has two contrary effects: One seems to be a subjective scarring effect of past unemployment, the other effect is not so clear: either people are too ashamed to admit their low re-employment expectations (to themselves or only to the interviewer is not clear), or they are indeed not informed about their actual low re-employment expectations given their unemployment experience.

Similarly, their are two types of people where for one type, a higher unemployment rate contributes to an underestimation and for the other type, the unemployment rate contributes to an overestimation.

7 Behavioral Response to Prediction Errors

7.1 Estimation Strategy

Having established that prediction errors exist and having identified the types of people who make prediction errors, the remaining question is whether these prediction errors have any behavioral consequences. If so, it might be important to inform people about their prediction errors in order to prevent them from making possibly damaging behavioral changes.

We investigate three types of behavioral responses that might occur among those who regain employment in t+1 or t+2. The first one is income (gross labor income per month). It could be that people who unrealistically fear that they have a low re-employment probability accept work at a lower income than those whho have more realistic re-employment expectations. Similarly they might work less hours and have a lower probability to work full-time. These are the other two outcomes we look at.

The other two behavioral responses that are investigated are dropping out of the labor force in t+1 or t+2 and job search effort in t. People who underestimate their re-employment probability might be more likely to drop out of the labor force and might not actively search for work if they think they have no chance to get re-employed to begin with.

We estimate the following equation

$$\begin{gathered} BehavioralResponse_{it} = \alpha + \delta w_{it} + X'_{it}\beta + \varepsilon_{it} \\ \varepsilon_{it} = \mu_i + \nu_{it} \end{gathered} \tag{9}$$

where the dependent variable is one of the five behavioral response variables, X'_{it} represents a vector of control variables (consisting of socio-demographic characteristics, labor market history, external labor market characteristics, previous job characteristics and personality traits as explained in the previous section), ε_{it} is a composite error term that consists of an individual-specific random effect μ_i and an idiosyncratic error ν_{it}. Correlated random effects models are estimated in which μ_i is allowed to be correlated with the explanatory variables of the form $\mu_i = \overline{x_i}\eta + \vartheta_{it}$ (Mundlak, 1978) in order to control for unobserved heterogeneity.

We estimate several versions of this model where the variable w_{it} is either the subjective re-employment probability (on a scale from 0 to 100%) or a dummy variable for underestimation or the prediction error itself. This will first inform us whether the subjective expectations are related to future behavioral responses, but also whether a prediction error increases the likelihood of a behavioral response.

In the case of the income and work hours variable, equation (9) is estimated by OLS, otherwise by logit regression. As we are now investigating behavioral responses, we also include the people in the analysis that will later drop out of the labor force in t+1 and t+2. These people had been excluded in the previous analsyis because the results for the objective re-employment probability should not have been biased due to behavioral responses. This increases the sampel size to 2691 observations. For the behavioral responses that relate to being re-employed in t+1 and t+2, we restrict the sample to those individuals who are re-employed in t+1 or t+2. This leaves us with 1189 observations.

7.2 Results

Panel A of Table 7 shows the relationship between the subjective re-employment probability and the 5 behavioral responses (the same set of control variables are included as in Table 6). We see that the subjective re-employment probability is indeed related to all behavioral responses. If the subjective re-employment probability increases from 40% to 60% for example (by 20 pp.), this is related to a higher income of 65 Euro per month, a 3 pp. (almost 5 percent) higher probability of being full-time employed and 0.6 more work hours per week among those who regain employment in t+1 or t+2. A 20 pp. higher subjective re-employment probability is also related to a 1.6 pp. (=7%) lower probability of dropping out of the labor force and a 1.2 pp. (=1.5%) higher probability of actively looking for a job.

[Insert Table 7 here]

Panel B shows the relationship between an underestimation of the re-employment probability and the 5 behavioral responses. Among those who regain employment, having underestimated the re-employment probability is related to a monthly income that is 121 Euro smaller, a 8 pp. (=12.6%) lower probability of being full-time employed and work hours that are on average 1.7 hours lower per week. Underestimation is also associated with a 5 pp. (=20%) higher probability to drop out of the labor force and negatively related to job seartch effort, although not significantly.

Panel C puts the size of the prediction error (positive prediction error=underestimation; negative prediction error=overestimation) in relation to the behavioral responses. If the prediction error is 20 pp. compared to 0 pp., this is associated among those who regain employment with an income that is 78 Euro smaller, a decreased likelihood of full-time employment that is 3.2 pp. (=5%) smaller and around half an hour of less work hours a week. This would also increase the likelihood of dropping out of the labor force by 2.2 pp. (=9.8%) and the probability of actively looking for a job by 1.2 pp. (=0.02%).

8 Conclusion

This paper shows that some people consistently under-estimate their re-employment probability once unemployed and that, contrary to what previous reserach has concluded, the informational content of subjective re-employment expectations is quite limited. In fact, our model performs better on average at predicting re-employment than the individuals themselves. The only information needed about the individuals to make a significantly better prediction on average is their previous unemployment experience.

We find a scarring effect of past unemployment as high unemployment experience is found to increase underestimation.

Underestimation is also found to be related to subsequent behavioral changes. People who underestimate their re-employment probability accept a lower wage, work fewer hours, are less likely to work full-time, are more likely to drop out of the labor force and less likely to actively search for a job.

This analysis lends itself to some important policy conclusions as it can inform policy makers which group of people is at risk of making prediction errors. People with high previous unemployment experience should be informed about their actual re-employment chances to prevent them from adverse behavior such as dropping out of the labor force.

Table 1: Model Based Subjective Reemployment Probability

	(1) OLS	(2) OLS RE	(3) CRE
Socio-demographics			
Male	5.8448***	5.5255***	6.5849***
	(1.5996)	(1.7314)	(1.8120)
Age	1.5209***	1.5798***	0.6206
	(0.4863)	(0.5022)	(1.3039)
Age squared/1000	-35.7361***	-37.3082***	-29.3686**
	(5.9097)	(6.1430)	(14.3762)
Yrs in Education	2.2239***	2.1531***	3.7370*
	(0.3828)	(0.4082)	(2.1162)
Is Married	-3.2268**	-2.9813*	-2.7096
	(1.5124)	(1.6314)	(4.3793)
Children	-0.3982	-1.1420	-2.7590
	(1.4447)	(1.4957)	(2.8472)
Home Owner	2.4065*	2.4567	2.2782
	(1.4239)	(1.5222)	(4.8079)
Labor Market History			
Part Time Exp	0.4702*	0.5585**	1.9562
	(0.2671)	(0.2829)	(1.7957)
Full Time Exp	0.4428***	0.4898***	0.7047
	(0.1666)	(0.1771)	(0.9085)
Unempl. Exp. 0.1-1.0yrs	-2.7230	-2.3614	-5.7652
	(2.6723)	(2.6160)	(3.9390)
Unempl. Exp. 1.1-3.0yrs	-4.4189*	-4.7993*	-6.1782
	(2.6546)	(2.6054)	(4.0679)
Unempl. Exp. 3.1-5.0yrs	-11.0784***	-10.4895***	-7.7320*
	(2.8892)	(2.8396)	(4.5638)
Unempl. Exp. 5+yrs	-17.5220***	-16.0915***	-10.1142*
	(3.0496)	(3.0594)	(5.3825)
Tenure last Job 3-9 Years?	-1.9024	-1.7993	-1.6005
	(1.9404)	(2.0069)	(3.9168)
Tenure last Job 10 or more Years?	-7.7139***	-7.7571***	-0.5395
	(2.4918)	(2.6128)	(5.8391)
External Labor Market			
Unempl Rate	-0.9942***	-0.9896***	-0.1926
	(0.1509)	(0.1598)	(0.5851)

Note: Year dummies are also included. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 1 (continued): Model Based Subjective Reemployment Probability

	(1) OLS	(2) OLS RE	(3) CRE
Previous Job Characteristics			
Was working in the Privat Sector	3.8546*	3.0921	2.4510
	(1.9999)	(2.0938)	(3.7152)
Was temporary employed	-1.4460	-1.4541	1.6142
	(1.6054)	(1.6399)	(2.7491)
More than 20 at last workplace	-0.5408	0.3510	2.9447
	(1.4614)	(1.4983)	(2.6617)
Log Last Income (Gross)	1.3130	1.3429	0.6436
	(0.9240)	(0.9189)	(1.2482)
Last ISEI Status	-0.0932	-0.1214	-0.0641
	(0.1207)	(0.1241)	(0.2506)
Managers/Professionals	0.3325	2.6589	-1.2659
	(6.3176)	(6.4599)	(12.5105)
Techn./Assoc. Profess.	2.0623	2.9565	-5.4063
	(4.3923)	(4.5500)	(9.4414)
Clerks	4.8523	6.3825	2.2491
	(3.8972)	(4.0513)	(7.9836)
Service/Shop Workers	4.5703	4.7296	5.3390
	(3.4047)	(3.5214)	(6.8317)
Agricult. Workers/Craft Workers	2.3530	3.8924	8.0913*
	(2.5194)	(2.6480)	(4.6778)
Machine Operators	5.2165*	6.5926**	16.9839***
	(3.0769)	(3.2510)	(6.4807)
Personality Traits			
Extraversion	-0.3977	-0.4269	-0.5368
	(0.7304)	(0.7902)	(0.7939)
Consienciousness	0.6822	0.7494	0.6763
	(0.7876)	(0.8626)	(0.8670)
Neuroticism	0.6613	0.6652	0.7236
	(0.7075)	(0.7645)	(0.7689)
Openess	2.2603***	2.0088**	1.9855**
	(0.7797)	(0.8438)	(0.8511)
Agreeability	-1.8968***	-1.7860**	-1.7396**
	(0.7342)	(0.8002)	(0.8089)
LOC	2.2934***	2.0709***	1.7166**
	(0.7094)	(0.7695)	(0.7846)
R2	0.367	0.366	0.378
Number of Observations	1669	1669	1669

Note: Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 2: Labor Force Status Model

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit CRE
Expectations					
Subjective Probability 10 - 20%	-0.0164	-0.0598	-0.0571	-0.0591	-0.1100
	(0.0600)	(0.0582)	(0.0580)	(0.0584)	(0.0750)
Subjective Probability 30 - 40%	0.0529	-0.0180	-0.0246	-0.0283	-0.0206
	(0.0562)	(0.0581)	(0.0578)	(0.0587)	(0.0748)
Subjective Probability 50 - 60%	0.1125**	0.0005	-0.0049	-0.0156	-0.0198
	(0.0470)	(0.0509)	(0.0513)	(0.0519)	(0.0699)
Subjective Probability 70 - 80%	0.2287***	0.0845	0.0611	0.0519	0.0218
	(0.0418)	(0.0528)	(0.0543)	(0.0556)	(0.0781)
Subjective Probability 90 - 100%	0.3699***	0.1830***	0.1573***	0.1444**	0.0277
	(0.0398)	(0.0540)	(0.0558)	(0.0571)	(0.0809)
Variables as in Dickersen and Green (2012)					
Male		-0.0258	0.0005	0.0091	0.0028
		(0.0227)	(0.0273)	(0.0290)	(0.0278)
Age		0.0008	0.0060	0.0071	0.0485**
		(0.0075)	(0.0082)	(0.0083)	(0.0202)
Age squared/1000		-0.0681	-0.1651*	-0.1800*	0.0594
		(0.0929)	(0.0995)	(0.1008)	(0.2283)
Yrs in Education		0.0183***	0.0159**	0.0132**	-0.0063
		(0.0060)	(0.0067)	(0.0066)	(0.0340)
Was working in the Privat Sector		0.0362	0.0641*	0.0623*	0.0961
		(0.0353)	(0.0354)	(0.0348)	(0.0638)
Was temporary employed		0.0299	0.0398	0.0429	-0.0854*
		(0.0264)	(0.0276)	(0.0277)	(0.0446)
More than 20 at last workplace		-0.0116	-0.0043	0.0034	0.0792*
		(0.0249)	(0.0248)	(0.0249)	(0.0443)
nerver obs. in empl.		-0.0669	0.0342	0.0003	0.1589
		(0.0485)	(0.1319)	(0.1359)	(0.1383)
Unemployment Experience		-0.0276***			
		(0.0041)			
Other Socio-demographics					
Is Married			0.0638**	0.0592**	-0.0103
			(0.0268)	(0.0271)	(0.0737)
Children			-0.0553**	-0.0604**	0.0002
			(0.0258)	(0.0257)	(0.0463)
Home Owner			0.0822***	0.0828***	0.0752
			(0.0252)	(0.0252)	(0.0797)
Other Labor Market History					
Part Time Exp			0.0011	0.0003	-0.1054***
			(0.0047)	(0.0045)	(0.0281)
Full Time Exp			0.0003	0.0003	-0.0897***
			(0.0030)	(0.0029)	(0.0151)
Unempl. Exp. 0.1-1.0yrs			0.0021	-0.0004	0.0634
			(0.0502)	(0.0496)	(0.0685)
Unempl. Exp. 1.1-3.0yrs			-0.0795*	-0.0752	0.1749***
			(0.0476)	(0.0467)	(0.0648)
Unempl. Exp. 3.1-5.0yrs			-0.0944*	-0.0852	0.2561***
			(0.0526)	(0.0518)	(0.0524)

Note: Marginal Effects. Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 2 (continued): Labor Force Status Model

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit CRE
Unempl. Exp. 5+yrs			-0.2487***	-0.2306***	0.1751***
			(0.0606)	(0.0604)	(0.0560)
Tenure last Job 3-9 Years?			0.0334	0.0329	0.1197*
			(0.0353)	(0.0354)	(0.0619)
Tenure last Job 10 or more Years?			-0.0715	-0.0581	0.2281***
			(0.0485)	(0.0468)	(0.0613)
External Labor Market					
Unempl Rate			-0.0063**	-0.0074***	-0.0266***
			(0.0027)	(0.0027)	(0.0097)
Previous Job Characteristics					
Log Last Income (Gross)			0.0190	0.0142	0.0132
			(0.0169)	(0.0168)	(0.0193)
Last ISEI Status			-0.0056**	-0.0057***	-0.0137***
			(0.0022)	(0.0022)	(0.0040)
Managers/Professionals			0.2697***	0.2753***	0.3515***
			(0.0619)	(0.0602)	(0.0585)
Techn./Assoc. Profess.			0.1921***	0.1870***	0.3401***
			(0.0600)	(0.0599)	(0.0631)
Clerks			0.2376***	0.2245***	0.3201***
			(0.0526)	(0.0550)	(0.0636)
Service/Shop Workers			0.1171**	0.1145**	0.0990
			(0.0473)	(0.0473)	(0.1033)
Agricult. Workers/Craft Workers			0.0586	0.0583	0.1469**
			(0.0409)	(0.0405)	(0.0670)
Machine Operators			0.0273	0.0138	0.1372
			(0.0498)	(0.0509)	(0.0867)
Personality					
Extraversion				0.0052	0.0090
				(0.0122)	(0.0118)
Consienciousness				0.0076	0.0047
				(0.0126)	(0.0130)
Neuroticism				-0.0058	-0.0168
				(0.0118)	(0.0115)
Openess				0.0054	-0.0052
				(0.0134)	(0.0126)
Agreeability				0.0124	0.0119
				(0.0127)	(0.0120)
LOC				0.0424***	0.0228*
				(0.0121)	(0.0117)
McKelvey and Zavoina's R2	0.146	0.232	0.278	0.297	0.530
McFadden's R2	0.088	0.140	0.167	0.178	
McFadden's Adj R2	0.078	0.122	0.132	0.137	
AIC	2047.309	1948.876	1926.199	1914.996	1635.168
BIC	2101.509	2051.855	2132.159	2153.476	2047.087
Log likelihood	-1013.654	-955.4378	-925.0997	-913.4982	-741.5841
Number of Observations	1669	1669	1669	1669	1669
Number of Cluster	1184	1184	1184	1184	

Note: Marginal Effects. Year dummies are also included. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

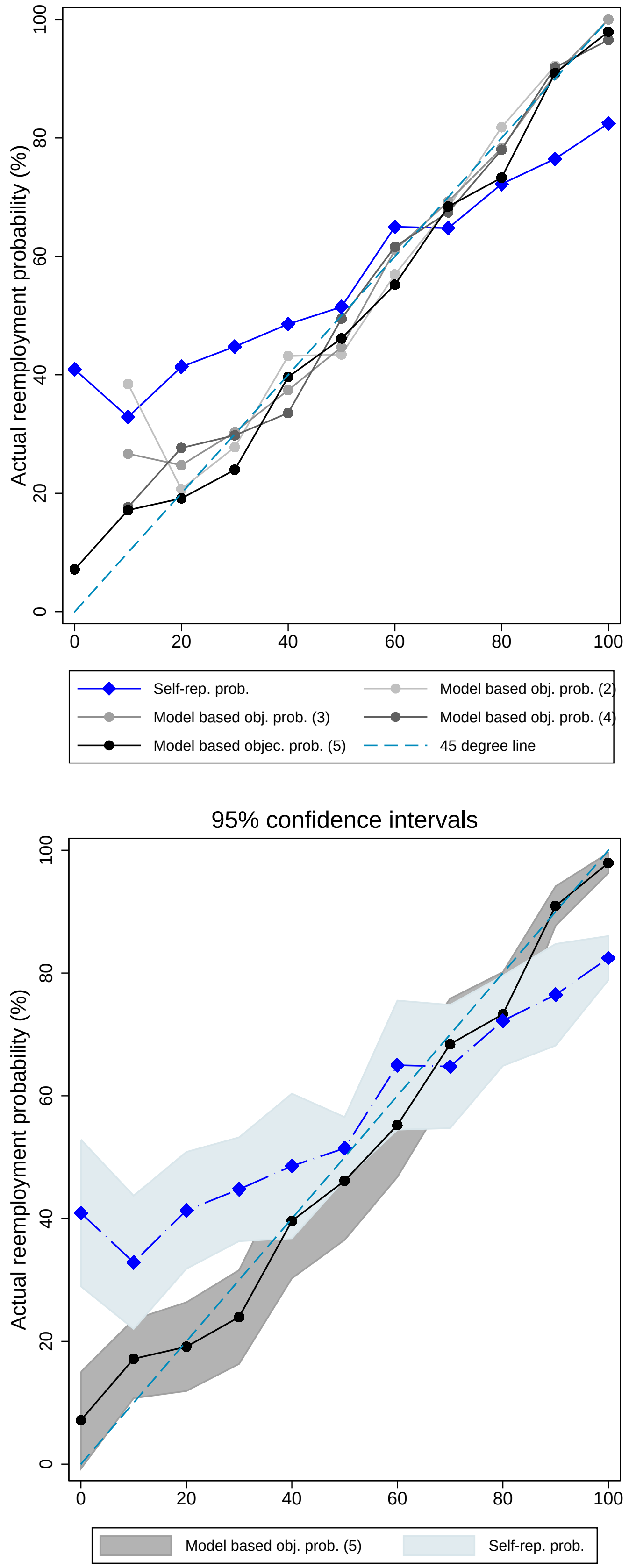

Figure 1: Perceived, Prediced and Actual Re-employment Probability

Table 3: Prediction-Realization Tables

		Predictions									
		(2) Model Based Obj. DG		(3) Model Based Obj. w/o Pers.		(4) Model Based Obj.		(5) Model Based Obj. (Mundlak)		Self-Rep.	
		0	1	0	1	0	1	0	1	0	1
Realization	0	0.2271	0.1564	0.2499	0.1336	0.2564	0.1270	0.2930	0.0905	0.2642	0.1192
	1	0.1624	0.4542	0.1690	0.4476	0.1660	0.4506	0.1186	0.4979	0.2283	0.3883
Sigma		0.3297		0.3785		0.3996		0.5683		0.3048	
		[0.2887,0.3707]		[0.3355,0.4214]		[0.3574,0.4417]		[0.5245,0.6121]		[0.2632,0.3464]	
Delta		0.3288		0.3775		0.3996		0.5716		0.3188	
		[0.2845,0.3732]		[0.3286,0.4264]		[0.3579,0.4412]		[0.5288,0.6145]		[0.2690,0.3686]	

Table 4: Minimum Information needed

Variables	Sigma	Std. Err.	Conf. Int. down	Conf. Int. up
(A) One Variable				
Unemployment Experience	.454001	.01907	.4166238	.4913781
(B) Two Variables				
Unempl. Exp., Temporary Employed	.4743572	.0214413	.4323324	.5163822
Unempl. Exp., Tenure	.4712647	.0209796	.4301446	.5123847
Unempl. Exp., ISEI Status	.4676614	.0219664	.4246072	.5107155
Unempl. Exp., Unemployment Rate	.4667763	.0212445	.4251371	.5084155
Unempl. Exp., Education	.4640192	.0237268	.4175146	.5105238
Unempl. Exp., Locus of Control	.4614452	.0193044	.4236086	.4992817
Unempl. Exp., Size of Company	.4609703	.019404	.4229385	.4990021
Unempl. Exp., Part Time Experience	.4595207	.0230482	.4143462	.5046952
Unempl. Exp., Full-Time Experience	.4589088	.0214041	.4169567	.5008609
Unempl. Exp., ISCO Occ. Code	.4583637	.0221282	.4149923	.501735
Unempl. Exp., Age	.4570537	.018546	.4207034	.4934039
Unempl. Exp., Income	.4559716	.0225504	.4117729	.5001704
Unempl. Exp., Private Sector	.4554956	.0208011	.4147254	.4962659
Unempl. Exp., Married	.4552005	.0251085	.4059878	.5044132
Unempl. Exp., Sex	.454001	.0228066	.4093001	.4987019
Unempl. Exp., Conscientiousness	.453588	.0234651	.4075965	.4995796
Unempl. Exp., Extraversion	.4527492	.024255	.4052094	.5002889
Unempl. Exp., Openness	.452568	.0200508	.4132684	.4918675
Unempl. Exp., Home Owner	.4501131	.0206337	.4096712	.4905551
Unempl. Exp., Children in HH	.4423237	.0181768	.4066971	.4779502
Unempl. Exp., Neuroticism	.4420112	.0230253	.3968816	.4871407
(C) Without Unemployment Experience				
Age, Unempl. Rate, ISCO Occ. Code	.3125879	.0228761	.2677507	.3574251
Age, Full-Time Exp., ISCO Occ. Code	.3054112	.0239261	.258516	.3523064

Table 5: **Under-, Exact and Overestimation**

	Coef.	Marginal Effects (ME)		
	(1)	(2)	(3)	(4)
	ordered logit	underestimation	exact estimation	overestimation
Socio-demographics				
Male	0.2801**	-0.0474**	0.0194*	0.0281**
	(0.1417)	(0.0241)	(0.0102)	(0.0143)
Age	0.0202	-0.0034	0.0013	0.0020
	(0.0399)	(0.0067)	(0.0027)	(0.0041)
Age squared/1000	-0.5141	0.0865	-0.0343	-0.0522
	(0.4841)	(0.0816)	(0.0326)	(0.0493)
Yrs in Education	0.0431	-0.0072	0.0029	0.0044
	(0.0339)	(0.0057)	(0.0023)	(0.0034)
Is Married	-0.3979***	0.0668***	-0.0263***	-0.0404***
	(0.1378)	(0.0229)	(0.0095)	(0.0142)
Children	0.0892	-0.0150	0.0059	0.0091
	(0.1300)	(0.0217)	(0.0083)	(0.0134)
Home Owner	-0.2136*	0.0367*	-0.0156	-0.0210*
	(0.1225)	(0.0214)	(0.0098)	(0.0118)
Labor Market History				
Part Time Exp	-0.0037	0.0006	-0.0002	-0.0004
	(0.0243)	(0.0041)	(0.0016)	(0.0025)
Full Time Exp	0.0095	-0.0016	0.0006	0.0010
	(0.0147)	(0.0025)	(0.0010)	(0.0015)
Unempl. Exp. 0.1-1.0yrs	-0.2360	0.0409	-0.0180	-0.0230
	(0.1747)	(0.0313)	(0.0151)	(0.0163)
Unempl. Exp. 1.1-3.0yrs	-0.2238	0.0385	-0.0165	-0.0220
	(0.1896)	(0.0335)	(0.0157)	(0.0179)
Unempl. Exp. 3.1-5.0yrs	-0.4878**	0.0883**	-0.0441*	-0.0442**
	(0.2167)	(0.0420)	(0.0251)	(0.0174)
Unempl. Exp. 5+yrs	-0.1146	0.0196	-0.0081	-0.0114
	(0.2375)	(0.0411)	(0.0180)	(0.0231)
Tenure last Job 3-9 Years?	-0.2360	0.0413	-0.0188	-0.0226
	(0.1688)	(0.0307)	(0.0157)	(0.0151)
Tenure last Job 10 or more Years?	-0.0771	0.0132	-0.0055	-0.0077
	(0.2290)	(0.0398)	(0.0176)	(0.0222)
External Labor Market				
Unempl Rate	-0.0185	0.0031	-0.0012	-0.0019
	(0.0123)	(0.0021)	(0.0009)	(0.0012)

Note: Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5 (continued): Under-, Exact and Overestimation

	Coef.	Marginal Effects (ME)		
	(1) ordered logit	(2) underestimation	(3) exact estimation	(4) overestimation
Previous Job Characteristics				
Was working in the Privat Sector	-0.0457	0.0077	-0.0030	-0.0047
	(0.1518)	(0.0253)	(0.0098)	(0.0156)
Was temporary employed	-0.2754**	0.0473**	-0.0201*	-0.0272**
	(0.1320)	(0.0231)	(0.0106)	(0.0128)
More than 20 at last workplace	-0.0298	0.0050	-0.0020	-0.0030
	(0.1253)	(0.0211)	(0.0084)	(0.0127)
Log Last Income (Gross)	-0.0167	0.0028	-0.0011	-0.0017
	(0.0696)	(0.0117)	(0.0046)	(0.0071)
Last ISEI Status	0.0150	-0.0025	0.0010	0.0015
	(0.0094)	(0.0016)	(0.0006)	(0.0010)
Managers/Professionals	-0.9954**	0.1982*	-0.1235	-0.0748***
	(0.4971)	(0.1101)	(0.0835)	(0.0272)
Techn./Assoc. Profess.	-0.6423*	0.1198*	-0.0646	-0.0552**
	(0.3508)	(0.0709)	(0.0459)	(0.0255)
Clerks	-0.5118	0.0947	-0.0501	-0.0446*
	(0.3312)	(0.0663)	(0.0419)	(0.0246)
1.Service/Shop Workers	-0.3646	0.0658	-0.0327	-0.0331
	(0.2758)	(0.0530)	(0.0309)	(0.0223)
Agricult. Workers/Craft Workers	-0.1791	0.0308	-0.0132	-0.0176
	(0.2138)	(0.0376)	(0.0172)	(0.0204)
Machine Operators	0.1581	-0.0257	0.0089	0.0168
	(0.2593)	(0.0408)	(0.0121)	(0.0288)
Personality Traits				
Extraversion	-0.0429	0.0072	-0.0029	-0.0044
	(0.0564)	(0.0095)	(0.0038)	(0.0057)
Consienciousness	-0.0165	0.0028	-0.0011	-0.0017
	(0.0636)	(0.0107)	(0.0042)	(0.0065)
Neuroticism	0.0726	-0.0122	0.0048	0.0074
	(0.0564)	(0.0095)	(0.0038)	(0.0057)
Openess	0.0379	-0.0064	0.0025	0.0038
	(0.0689)	(0.0116)	(0.0046)	(0.0070)
Agreeability	-0.1332**	0.0224**	-0.0089**	-0.0135**
	(0.0643)	(0.0108)	(0.0045)	(0.0065)
LOC	-0.0541	0.0091	-0.0036	-0.0055
	(0.0624)	(0.0105)	(0.0042)	(0.0064)
McKelvey and Zavoina's R2	0.079	0.079	0.079	0.079
Number of Observations	1669	1669	1669	1669
Number of Cluster	1184	1184	1184	1184

Note: Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 6: Determinants of Size of Prediction Error

	OLS	Q25	Q50	Q75
Socio-demographics				
Male	-3.7105	-3.4007	0.8301	-9.8713*
	(3.2159)	(6.5134)	(2.3337)	(5.0844)
Age	-0.5161	-2.3493	0.2333	-0.6724
	(0.9033)	(1.9559)	(0.6947)	(1.5213)
Age squared/1000	9.8929	15.4614	-12.4693	22.4058
	(11.1136)	(23.7226)	(8.6208)	(18.5876)
Yrs in Education	-0.4954	0.5350	1.2677**	-1.0045
	(0.7280)	(1.5652)	(0.5521)	(1.2490)
Is Married	8.6391***	15.5821**	4.5083*	14.3490***
	(3.1392)	(6.6863)	(2.3189)	(4.8181)
Children	-5.9780**	-19.4009***	-6.3798***	0.3983
	(2.8719)	(6.1360)	(2.1407)	(4.6262)
Home Owner	6.4417**	11.1388*	6.2952***	5.2583
	(2.7918)	(5.6900)	(2.0522)	(4.6010)
Labor Market History				
Part Time Exp	-0.3680	-0.6955	-0.0573	0.1439
	(0.5530)	(1.1820)	(0.4103)	(0.9400)
Full Time Exp	-0.3291	0.3525	0.1020	-0.6761
	(0.3442)	(0.7455)	(0.2644)	(0.5380)
Unempl. Exp. 0.1-1.0yrs	2.1836	-3.1034	0.4630	16.8421**
	(4.2651)	(9.1742)	(3.3651)	(7.3058)
Unempl. Exp. 1.1-3.0yrs	-2.8513	-15.7914	-5.1449	16.1400**
	(4.5199)	(9.7526)	(3.5060)	(7.2928)
Unempl. Exp. 3.1-5.0yrs	0.2488	-16.9499	-8.2068**	28.9125***
	(5.0710)	(11.1630)	(4.0073)	(8.4344)
Unempl. Exp. 5+yrs	-9.6461*	-24.7677**	-18.1277***	7.8667
	(5.5243)	(12.4393)	(4.3825)	(8.8361)
Tenure last Job 3-9 Years?	4.5189	9.6036	1.7309	3.0645
	(3.6565)	(7.7378)	(2.7934)	(6.3011)
Tenure last Job 10 or more Years?	-0.3737	-1.5968	-5.4063	4.8694
	(5.1611)	(10.2836)	(3.6945)	(8.1281)
External Labor Market				
Unempl Rate	0.0462	-1.4541**	-0.7538***	1.6000***
	(0.2790)	(0.6229)	(0.2180)	(0.4565)

Note: OLS and Unconditional Quantile Regressions. Marginal Effects. Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 6 (continued): Determinants of Size of Prediction Error

	OLS	Q25	Q50	Q75
Previous Job Characteristics				
Was working in the Privat Sector	3.1515	0.6714	4.7893	7.5372
	(3.7189)	(7.9949)	(2.9386)	(6.2795)
Was temporary employed	5.2283*	6.5924	2.2836	4.9247
	(2.8965)	(6.3415)	(2.2388)	(4.8536)
More than 20 at last workplace	0.8791	2.9347	1.1135	-2.5901
	(2.8340)	(6.0409)	(2.1264)	(4.7184)
Log Last Income (Gross)	0.6396	2.0507	1.3547*	0.1015
	(0.8925)	(2.0393)	(0.7181)	(1.4891)
Last ISEI Status	-0.4698**	-0.7767*	-0.4444***	-0.6722*
	(0.2097)	(0.4354)	(0.1592)	(0.3600)
Managers/Professionals	31.7801***	55.3741**	25.2195***	39.5607**
	(11.2137)	(22.8666)	(8.4850)	(19.7814)
Techn./Assoc. Profess.	17.6561**	30.9636*	14.4050**	29.3610**
	(8.0651)	(16.7742)	(6.0246)	(14.0050)
Clerks	20.5711***	40.0677***	20.2476***	20.3329*
	(7.7463)	(15.4304)	(5.3670)	(12.1464)
Service/Shop Workers	8.2792	15.2301	8.6643*	12.0621
	(6.2191)	(13.8542)	(4.8840)	(11.1222)
Agricult. Workers/Craft Workers	4.7048	13.4486	5.5034	13.1127*
	(4.8212)	(11.1118)	(3.8633)	(7.9658)
Machine Operators	-2.0064	4.3221	3.3652	-3.6681
	(6.0171)	(13.6294)	(4.7441)	(9.2784)
Personality Traits				
Extraversion	0.6563	-0.6870	0.5246	1.7721
	(1.3118)	(2.9791)	(1.0654)	(2.3081)
Consienciousness	0.5816	1.0001	1.4046	-0.3150
	(1.4030)	(3.2954)	(1.1786)	(2.5690)
Neuroticism	-1.0141	0.9967	0.2998	-4.6124**
	(1.2782)	(2.9977)	(1.0506)	(2.2011)
Openess	-1.0661	1.7370	0.9207	-4.1417
	(1.5011)	(3.2053)	(1.1532)	(2.6012)
Agreeability	2.5460*	-0.1552	0.5622	5.9760**
	(1.4248)	(3.0890)	(1.0891)	(2.3895)
LOC	2.3416*	8.0376***	3.7814***	-0.4830
	(1.3800)	(2.9956)	(1.0560)	(2.3393)
R2	0.055	0.056	0.153	0.069
Number of Observations	1669	1669	1669	1669

Note: OLS and Unconditional Quantile Regressions. Marginal Effects. Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 7: Behavioral Reponse

	UE in t, Empl in t+1/t+2			UE in t (incl. future dropouts)	
	(1) Income	(2) FT Empl.	(3) Work Hours	(4) Dropping OLF	(5) Job Search
Panel A					
Subj Re-Empl Prob	3.2565***	0.0015***	0.0311***	-0.0008***	0.0006*
	(0.8918)	(0.0005)	(0.0113)	(0.0003)	(0.0003)
R2	0.380		0.303		
McKelvey and Zavoina's R2		0.457		0.154	0.175
Number of Observations	1189	1189	1189	2691	2691
Panel B					
Underestimation	-121.4894***	-0.0798***	-1.7080***	0.0505***	-0.0192
	(45.0849)	(0.0281)	(0.5725)	(0.0181)	(0.0184)
R2	0.377		0.304		
McKelvey and Zavoina's R2		0.453		0.155	0.173
Number of Observations	1189	1189	1189	2691	2691
Panel C					
Prediction Error	-3.9237***	-0.0016***	-0.0256**	0.0011***	-0.0006*
	(0.9776)	(0.0006)	(0.0127)	(0.0003)	(0.0003)
R2	0.382		0.301		
McKelvey and Zavoina's R2		0.455		0.155	0.175
Number of Observations	1189	1189	1189	2691	2691

Note: Marginal Effects. Same control variables as in Table 6. Year dummies are also included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

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9 Appendix

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Employed in t+1 or t+2	0.62	0.49	0	1
Male	0.53	0.5	0	1
Age	40.37	11.15	17	63
Age squared/1000	1.75	0.89	0.29	3.97
Yrs in Education	11.42	2.1	7	18
Is Married	0.53	0.5	0	1
Children	0.43	0.49	0	1
Home Owner	0.32	0.47	0	1
Part Time Exp	1.32	3.32	0	30.7
Full Time Exp	13.49	10.69	0	43.8
Unemployment Experience	3.5	3.33	0	21.5
Tenure last Job 3-9 Years?	0.14	0.35	0	1
Tenure last Job 10 or more Years?	0.09	0.28	0	1
Unempl Rate	13.28	4.77	4.8	20.5
Was working in the Privat Sector	0.67	0.47	0	1
Was temporary employed	0.36	0.48	0	1
More than 20 at last workplace	0.49	0.5	0	1
Log Last Income (Gross)	5.8	2.9	0	9.69
Last ISEI Status	29.87	19.15	0	90
Managers/Professionals	0.07	0.26	0	1
Techn./Assoc. Profess.	0.13	0.34	0	1
Clerks	0.09	0.28	0	1
Service/Shop Workers	0.08	0.27	0	1
Agricult. Workers/Craft Workers	0.24	0.42	0	1
Machine Operators	0.09	0.28	0	1
nerver obs. in empl.	0.19	0.39	0	1
Extraversion	-0.02	0.96	-3.58	2.43
Consienciousness	0.08	0.95	-3.59	1.8
Neuroticism	0.1	0.94	-2.58	2.9
Openess	-0.14	0.93	-4.12	3.09
Agreeability	-0.02	1	-4.21	2.31
LOC	-0.42	0.98	-3.1	2.48
N		1669		

Table 2: Realisation-Prediction Sigma by 0/1-Coding Variation, Self-Reported Subjective Probability

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-3.953** (0.556) [39; 601] [27; 1002]	**-3.953** (0.695) [39; 601] [27; 1002]	**-3.576** (0.536) [39; 552] [27; 978]	**-3.106** (0.476) [39; 491] [27; 935]	**-2.535** (0.426) [39; 417] [27; 875]	**-2.258** (0.444) [39; 381] [27; 841]	**-0.846** (0.286) [39; 199] [27; 648]	**-0.629** (0.194) [39; 171] [27; 596]	**-0.388** (0.189) [39; 140] [27; 539]	**-0.081** (0.145) [39; 100] [27; 435]	**0.101** (0.084) [39; 76] [27; 357]
< 10		**-3.953** (0.634) [39; 601] [27; 1002]	**-3.576** (0.523) [39; 552] [27; 978]	**-3.106** (0.586) [39; 491] [27; 935]	**-2.535** (0.407) [39; 417] [27; 875]	**-2.258** (0.421) [39; 381] [27; 841]	**-0.846** (0.228) [39; 199] [27; 648]	**-0.629** (0.208) [39; 171] [27; 596]	**-0.388** (0.151) [39; 140] [27; 539]	**-0.081** (0.147) [39; 100] [27; 435]	**0.101** (0.113) [39; 76] [27; 357]
< 20			**-1.366** (0.214) [88; 552] [51; 978]	**-1.140** (0.178) [88; 491] [51; 935]	**-0.865** (0.147) [88; 417] [51; 875]	**-0.731** (0.117) [88; 381] [51; 841]	**-0.047** (0.079) [88; 199] [51; 648]	**0.057** (0.076) [88; 171] [51; 596]	**0.172** (0.058) [88; 140] [51; 539]	**0.316** (0.059) [88; 100] [51; 435]	**0.397** (0.047) [88; 76] [51; 357]
< 30				**-0.409** (0.079) [149; 491] [94; 935]	**-0.249** (0.080) [149; 417] [94; 875]	**-0.172** (0.070) [149; 381] [94; 841]	**0.224** (0.048) [149; 199] [94; 648]	**0.282** (0.047) [149; 171] [94; 596]	**0.346** (0.045) [149; 140] [94; 539]	**0.420** (0.034) [149; 100] [94; 435]	**0.454** (0.038) [149; 76] [94; 357]
< 40					**0.022** (0.037) [223; 417] [154; 875]	**0.072** (0.042) [223; 381] [154; 841]	**0.323** (0.034) [223; 199] [154; 648]	**0.357** (0.033) [223; 171] [154; 596]	**0.394** (0.027) [223; 140] [154; 539]	**0.426** (0.035) [223; 100] [154; 435]	**0.429** (0.032) [223; 76] [154; 357]
< 50						**0.131** (0.038) [259; 381] [188; 841]	**0.339** (0.025) [259; 199] [188; 648]	**0.364** (0.032) [259; 171] [188; 596]	**0.392** (0.027) [259; 140] [188; 539]	**0.409** (0.028) [259; 100] [188; 435]	**0.400** (0.032) [259; 76] [188; 357]
< 60							**0.305** (0.023) [441; 199] [381; 648]	**0.304** (0.021) [441; 171] [381; 596]	**0.299** (0.027) [441; 140] [381; 539]	**0.258** (0.031) [441; 100] [381; 435]	**0.194** (0.038) [441; 76] [381; 357]
< 70								**0.271** (0.023) [469; 171] [433; 596]	**0.260** (0.026) [469; 140] [433; 539]	**0.206** (0.028) [469; 100] [433; 435]	**0.130** (0.036) [469; 76] [433; 357]
< 80									**0.218** (0.026) [500; 140] [490; 539]	**0.151** (0.034) [500; 100] [490; 435]	**0.061** (0.042) [500; 76] [490; 357]
< 90										**0.045** (0.034) [540; 100] [594; 435]	**-0.069** (0.049) [540; 76] [594; 357]
< 100											**-0.166** (0.057) [564; 76] [672; 357]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]

Table 3: Realisation-Prediction Sigma by 0/1-Coding Variation, Model Based Objective Probability (Mundlak)

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-318.692** (94.888) [1; 639] [0; 1029]	**-276.177** (78.735) [1; 554] [0; 1014]	**-213.151** (59.951) [1; 428] [0; 993]	**-170.131** (53.142) [1; 342] [0; 967]	**-133.112** (36.921) [1; 268] [0; 931]	**-104.596** (34.069) [1; 211] [0; 892]	**-74.577** (20.559) [1; 151] [0; 831]	**-46.056** (13.348) [1; 94] [0; 738]	**-30.044** (8.457) [1; 62] [0; 641]	**-9.522** (3.898) [1; 21] [0; 452]	**1.000** (0.000) [1; 0] [0; 11]
< 10		**-1.998** (0.351) [86; 554] [15; 1014]	**-1.349** (0.231) [86; 428] [15; 993]	**-0.904** (0.208) [86; 342] [15; 967]	**-0.519** (0.149) [86; 268] [15; 931]	**-0.221** (0.121) [86; 211] [15; 892]	**0.094** (0.095) [86; 151] [15; 831]	**0.395** (0.083) [86; 94] [15; 738]	**0.564** (0.053) [86; 62] [15; 641]	**0.784** (0.047) [86; 21] [15; 452]	**0.244** (0.455) [86; 0] [15; 11]
< 20			**-0.099** (0.081) [212; 428] [36; 993]	**0.094** (0.063) [212; 342] [36; 967]	**0.260** (0.058) [212; 268] [36; 931]	**0.390** (0.048) [212; 211] [36; 892]	**0.528** (0.032) [212; 151] [36; 831]	**0.660** (0.030) [212; 94] [36; 738]	**0.733** (0.024) [212; 62] [36; 641]	**0.825** (0.021) [212; 21] [36; 452]	**-0.709** (0.627) [212; 0] [36; 11]
< 30				**0.285** (0.045) [298; 342] [62; 967]	**0.404** (0.033) [298; 268] [62; 931]	**0.497** (0.029) [298; 211] [62; 892]	**0.596** (0.029) [298; 151] [62; 831]	**0.690** (0.025) [298; 94] [62; 738]	**0.740** (0.021) [298; 62] [62; 641]	**0.797** (0.019) [298; 21] [62; 452]	**-1.904** (1.214) [298; 0] [62; 11]
< 40					**0.458** (0.030) [372; 268] [98; 931]	**0.531** (0.030) [372; 211] [98; 892]	**0.608** (0.026) [372; 151] [98; 831]	**0.680** (0.027) [372; 94] [98; 738]	**0.716** (0.018) [372; 62] [98; 641]	**0.748** (0.019) [372; 21] [98; 452]	**-3.559** (1.745) [372; 0] [98; 11]
< 50						**0.535** (0.022) [429; 211] [137; 892]	**0.599** (0.021) [429; 151] [137; 831]	**0.657** (0.025) [429; 94] [137; 738]	**0.683** (0.021) [429; 62] [137; 641]	**0.693** (0.023) [429; 21] [137; 452]	**-5.348** (2.538) [429; 0] [137; 11]
< 60							**0.568** (0.019) [489; 151] [198; 831]	**0.612** (0.017) [489; 94] [198; 738]	**0.626** (0.020) [489; 62] [198; 641]	**0.609** (0.027) [489; 21] [198; 452]	**-8.144** (2.907) [489; 0] [198; 11]
< 70								**0.539** (0.022) [546; 94] [291; 738]	**0.538** (0.025) [546; 62] [291; 641]	**0.484** (0.027) [546; 21] [291; 452]	**-12.401** (4.669) [546; 0] [291; 11]
< 80									**0.447** (0.019) [578; 62] [388; 641]	**0.356** (0.032) [578; 21] [388; 452]	**-16.837** (7.963) [578; 0] [388; 11]
< 90										**0.118** (0.044) [619; 21] [577; 452]	**-25.468** (6.458) [619; 0] [577; 11]
< 100											**-45.580** (22.066) [640; 0] [1018; 11]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]

Table 4: Realisation-Prediction Adj.Sigma by 0/1-Coding Variation, Self-Reported Subjective Probability

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-3.953** (0.623) [39; 601] [27; 1002]	**-3.953** (0.615) [39; 601] [27; 1002]	**-3.910** (0.683) [39; 552] [27; 978]	**-3.886** (0.723) [39; 491] [27; 935]	**-3.830** (0.547) [39; 417] [27; 875]	**-3.791** (0.574) [39; 381] [27; 841]	**-2.826** (0.912) [39; 199] [27; 648]	**-2.525** (0.783) [39; 171] [27; 596]	**-1.948** (0.791) [39; 140] [27; 539]	**-0.623** (0.920) [39; 100] [27; 435]	**0.009** (0.421) [39; 76] [27; 357]
< 10		**-3.953** (0.528) [39; 601] [27; 1002]	**-3.910** (0.635) [39; 552] [27; 978]	**-3.886** (0.650) [39; 491] [27; 935]	**-3.830** (0.597) [39; 417] [27; 875]	**-3.791** (0.662) [39; 381] [27; 841]	**-2.826** (0.824) [39; 199] [27; 648]	**-2.525** (0.786) [39; 171] [27; 596]	**-1.948** (0.890) [39; 140] [27; 539]	**-0.623** (0.561) [39; 100] [27; 435]	**0.009** (0.435) [39; 76] [27; 357]
< 20			**-1.366** (0.197) [88; 552] [51; 978]	**-1.296** (0.213) [88; 491] [51; 935]	**-1.176** (0.184) [88; 417] [51; 875]	**-1.099** (0.223) [88; 381] [51; 841]	**-0.134** (0.182) [88; 199] [51; 648]	**0.017** (0.116) [88; 171] [51; 596]	**0.041** (0.013) [88; 140] [51; 539]	**0.051** (0.011) [88; 100] [51; 435]	**0.047** (0.008) [88; 76] [51; 357]
< 30				**-0.409** (0.079) [149; 491] [94; 935]	**-0.295** (0.077) [149; 417] [94; 875]	**-0.223** (0.097) [149; 381] [94; 841]	**0.096** (0.019) [149; 199] [94; 648]	**0.103** (0.016) [149; 171] [94; 596]	**0.106** (0.013) [149; 140] [94; 539]	**0.091** (0.009) [149; 100] [94; 435]	**0.074** (0.007) [149; 76] [94; 357]
< 40					**0.022** (0.046) [223; 417] [154; 875]	**0.066** (0.040) [223; 381] [154; 841]	**0.174** (0.018) [223; 199] [154; 648]	**0.168** (0.015) [223; 171] [154; 596]	**0.158** (0.012) [223; 140] [154; 539]	**0.127** (0.011) [223; 100] [154; 435]	**0.101** (0.009) [223; 76] [154; 357]
< 50						**0.131** (0.035) [259; 381] [188; 841]	**0.204** (0.014) [259; 199] [188; 648]	**0.193** (0.019) [259; 171] [188; 596]	**0.178** (0.015) [259; 140] [188; 539]	**0.141** (0.013) [259; 100] [188; 435]	**0.111** (0.011) [259; 76] [188; 357]
< 60							**0.305** (0.024) [441; 199] [381; 648]	**0.276** (0.020) [441; 171] [381; 596]	**0.242** (0.023) [441; 140] [381; 539]	**0.170** (0.027) [441; 100] [381; 435]	**0.110** (0.024) [441; 76] [381; 357]
< 70								**0.271** (0.024) [469; 171] [433; 596]	**0.234** (0.025) [469; 140] [433; 539]	**0.153** (0.031) [469; 100] [433; 435]	**0.083** (0.027) [469; 76] [433; 357]
< 80									**0.218** (0.024) [500; 140] [490; 539]	**0.126** (0.029) [500; 100] [490; 435]	**0.044** (0.039) [500; 76] [490; 357]
< 90										**0.045** (0.030) [540; 100] [594; 435]	**-0.078** (0.058) [540; 76] [594; 357]
< 100											**-0.166** (0.054) [564; 76] [672; 357]

Notes: In each cell: Sigma, (standard error), $[n_{11};n_{21}]$ $[n_{21};n_{22}]$

Table 5: Realisation-Prediction Adj.Sigma by 0/1-Coding Variation, Model Based Objective Probability (Mundlak)

x \ y	>0	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
= 0	**-318.692** (93.419) [1; 639] [0; 1029]	**-312.503** (85.664) [1; 554] [0; 1014]	**-293.630** (72.742) [1; 428] [0; 993]	**-276.155** (87.949) [1; 342] [0; 967]	**-257.494** (77.942) [1; 268] [0; 931]	**-239.050** (65.513) [1; 211] [0; 892]	**-214.986** (61.211) [1; 151] [0; 831]	**-184.890** (53.269) [1; 94] [0; 738]	**-168.860** (53.097) [1; 62] [0; 641]	**-118.057** (43.633) [1; 21] [0; 452]	**0.000** (0.000) [1; 0] [0; 11]
< 10		**-1.998** (0.308) [86; 554] [15; 1014]	**-1.622** (0.283) [86; 428] [15; 993]	**-1.266** (0.255) [86; 342] [15; 967]	**-0.855** (0.289) [86; 268] [15; 931]	**-0.425** (0.232) [86; 211] [15; 892]	**0.039** (0.090) [86; 151] [15; 831]	**0.123** (0.019) [86; 94] [15; 738]	**0.131** (0.013) [86; 62] [15; 641]	**0.093** (0.008) [86; 21] [15; 452]	**0.001** (30.571) [86; 0] [15; 11]
< 20			**-0.099** (0.065) [212; 428] [36; 993]	**0.081** (0.055) [212; 342] [36; 967]	**0.196** (0.037) [212; 268] [36; 931]	**0.256** (0.033) [212; 211] [36; 892]	**0.287** (0.024) [212; 151] [36; 831]	**0.276** (0.017) [212; 94] [36; 738]	**0.238** (0.013) [212; 62] [36; 641]	**0.154** (0.010) [212; 21] [36; 452]	**-29.439** (33.111) [212; 0] [36; 11]
< 30				**0.285** (0.048) [298; 342] [62; 967]	**0.353** (0.029) [298; 268] [62; 931]	**0.382** (0.022) [298; 211] [62; 892]	**0.385** (0.018) [298; 151] [62; 831]	**0.352** (0.016) [298; 94] [62; 738]	**0.300** (0.013) [298; 62] [62; 641]	**0.199** (0.011) [298; 21] [62; 452]	**-38.539** (20.252) [298; 0] [62; 11]
< 40					**0.458** (0.024) [372; 268] [98; 931]	**0.472** (0.022) [372; 211] [98; 892]	**0.460** (0.015) [372; 151] [98; 831]	**0.414** (0.016) [372; 94] [98; 738]	**0.354** (0.017) [372; 62] [98; 641]	**0.239** (0.010) [372; 21] [98; 452]	**-42.848** (20.301) [372; 0] [98; 11]
< 50						**0.535** (0.024) [429; 211] [137; 892]	**0.515** (0.018) [429; 151] [137; 831]	**0.461** (0.017) [429; 94] [137; 738]	**0.395** (0.013) [429; 62] [137; 641]	**0.269** (0.012) [429; 21] [137; 452]	**-44.748** (19.399) [429; 0] [137; 11]
< 60							**0.568** (0.023) [489; 151] [198; 831]	**0.507** (0.019) [489; 94] [198; 738]	**0.434** (0.017) [489; 62] [198; 641]	**0.294** (0.016) [489; 21] [198; 452]	**-46.563** (31.483) [489; 0] [198; 11]
< 70								**0.539** (0.024) [546; 94] [291; 738]	**0.458** (0.021) [546; 62] [291; 641]	**0.298** (0.020) [546; 21] [291; 452]	**-48.038** (17.485) [546; 0] [291; 11]
< 80									**0.447** (0.025) [578; 62] [388; 641]	**0.265** (0.025) [578; 21] [388; 452]	**-49.135** (18.679) [578; 0] [388; 11]
< 90										**0.118** (0.040) [619; 21] [577; 452]	**-48.697** (16.527) [619; 0] [577; 11]
< 100											**-45.580** (24.710) [640; 0] [1018; 11]

Notes: In each cell: Sigma, (standard error), [n_{11};n_{21}] [n_{21};n_{22}]